Distributed Algorithms for Peer-to-Peer Energy Trading

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Declaration of Authorship

I, Olamide JOGUNOLA, declare that this thesis titled, "Distributed Algorithms for Peer-to-Peer Energy Trading" and the work presented in it are my own. I confirm that:

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- Where I have consulted the published work of others, this is always clearly attributed.
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Abstract

As the proliferation of the 'sharing economy' increases, its phenomenon is actively extending to the power grid, where energy consumers are motivated to use, produce, trade or share energy with the main grid and themselves. To optimise the potential of this changing era in smart grid, considering the complexity requirements of the individual distributed connected components, a distributed coordination algorithm is required to manage the large influx of energy as well as the altruistic goal of diverse energy producers. Furthermore, a trading platform is actively needed to implement these distributed algorithms to match the prosumers, coordinate their resources and maximise their utilities for increased profits and cost savings. This research investigates distributed algorithms for peer-to-peer energy trading and sharing (P2P-ETS) to facilitate discovery, communication and utility maximisation of peers who are trading energy in a P2P fashion.

To begin, a four-layer system architectural model is proposed to categorise the key elements and technologies associated with the P2P-ETS. Then, constrained by as few assumptions as possible, while showing promising performance and key metrics, three distributed algorithms are developed to facilitate discovery, peer's matching, data routing, energy transfer, and utility maximisation of the trading entities. These algorithms utilise only local information to solve the problem with promising results, complementing their presentation with simulations that demonstrate their effectiveness over imperfect communication links.

Finally, based on these distributed algorithms, a software platform is developed to support the pairing of prosumers on the P2P-ETS platform. A case study based on real microgrid data is used to verify the performance of the platform which demonstrate increase in local energy consumption. Simulation results show that the developed platform is able to balance local generation and consumption and increase cost savings of 45% for prosumers that trade energy among themselves compared to trading with the power grid. This savings however varies depending on the participants on the platform.

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Contents

List of Figures

List of Tables

List of Abbreviations

3G/4G/5G Third/Fourth/Fifth Generation

ACO Ant Colony Optimisation

BB-PLC Broadband Power Line Communication

CPN Customer Premises Network

CPP Critical Peak Pricing

DAP Distributed Adaptive Primal

DCS Distribution Customer Storage

DDG Distributed Dual Gradient

DEG Distributed Energy Generation

DER Distributed Energy Resources

DG Distributed Generation

DR Demand Response

DSL Digital Subscriber Line

DSO Distribution Service Operator

EDP Economic Dispatch Problem

ED Economic Dispatch

ESM Energy Sharing Model

ESP Energy Sharing Provider

ESS Energy Storage System

ETS Energy Trading Structure

EV Electric Vehicle

FAN Field Area Network

FPP Federated Power Plant

G2V Grid-to-Vehicle

GHE Greenhouse gas Emissions

HALO Hop-by-hop adaptive state routing algorithm

HAN Home Area Network

HEMS Home Energy Management System

IBR Inclining Block Rate

ICC Incremental Cost Consensus

ICT Information Communication Technology

IEEE Institutes of Electrical and Electronics Engineers

IPPA Improved Physarum Polycephalum algorithm

ITU International Telecommunication Union

KPI Key Performance Indicator

LANs Local Area Networks

MCF Multi-commodity flow

MDMS Meter Data Management System

MG Microgrid

NAN Neighbourhood Area Network

NB-PLC Narrowband Power Line Communication

Ofgem Office of Gas and Electricity Market

P2P-ETS Peer-to-Peer Energy Trading and Sharing

P2P Peer-to-Peer

PLC Power Line Communication

QoE Quality of Experience

QoS Quality of Service

RTP Real-Time Pricing

SGAM Smart grid Architectural model

SONA Service Oriented Network Architecture

SPoF Single Point of Failure

TCP/IP Transmission control protocol/internet protocol

TOU Time-of-Use

UNB-PLC Ultra-narrowband Power Line Communication

V2G Vehicle-to-Grid

VAT Value Added Tax

VDSL Very-high-data rate Digital Subscriber Line

VMG Virtual Microgrid

WAN Wide Area Network

Wi-Fi Wireless-Fidelity

WiMAX Worldwide Interoperability for Microwave Access

WPAN Wireless Personal Area Network

Nomenclature

α	The fairness parameter associated to a user.
α_t	The step size at time t.
$\bar{\Phi}_{i,j}(x_{i,j})$	Cost of path P to send a message from n_i to n_j.
$\bar{k}_{i,j}$	Message signal delay on link (i,j).
$\bar{l}_{i,j}$	Link utilization indicator for each link in the network.
$\bar{M}$	A subset of E of the graph G.
$\bar{p}$	The price of electricity.
ℓ	Langrangian dual variable of optimal resource allocation.
γ	A constant representing the decay rate of the tube.
$\lambda_{ij,k}$	Incremental cost per unit energy generated and transferred using link (i,j).
$\mathbf{A}_{i,j}$	Weights on link (i,j).
$\mathcal{L},\mathcal{F},\mathcal{J}$	The Lagrangian multipliers.
ω	The weight associated to the fairness parameter of users.
$\Phi_{i,j}(x_{i,j})$	Cost function associated to link (i,j).
θ	A constant introduced for maximising the utility function.
A_j	The link between prosumers n_i and n_j in the network of m^{th} cluster.
$C_i(.)$	Energy cost function of prosumer n_i.

$c_{i,j}, c_l$ Capacity on link (i, j).

$C_{ij,k}(x_{ij,k})$ Energy cost function of flow in arcs (i, j).

D Total energy demand on the network.

$D_{i,j}$ The conductivity/total traffic of the tube/link.

d_{ij} Local energy demand at each bus.

E Set of network links (i, j) connecting the prosumers.

$f_{i,j}$ Signal loss probability on link (i, j).

$G(t)$ The time-varying network graph.

$g(t)$ The (sub)gradient to Lagrange dual problem $\lambda(t)$.

G^* A subgragh of G.

$g_i(q_i)$ The conjugate convex function.

I_n Ingress link to an intermediary or destination peer n_j.

I_o A constant flux/energy demand flowing from the n_i to n_j.

J Social welfare.

$k \in K$ Messages from different peers in the network.

L The length of the tube.

$l_{i,j}$ Lower bounds of energy flow capacity on link i, j.

M Virtual microgrid clusters.

$n \in N$ Actors (prosumer, consumer or producer).

n_j Set of actors.

$N_{\bar{k}}$ The type of group of actors on the P2P-ETS platform.

$O(n)$	Order of n.
p_i, p_j	The pressure at n_i and n_j.
$P(i,j)$	set of all paths from prosumer n_i to n_j.
R	A vertex cover of size $\lvert\bar{M}\rvert$ in $G^*_{N_i,N_j}$.
$S, \bar{T}$	Actors/nodes in R.
$t \in T$	Algorithm iteration time.
$U(x_i)$	Weighted utility model for prosumers.
U_n	Egress link from a source or intermediary peer n_i.
$u_{i,j}$	Upper bounds of energy flow capacity on link i, j.
V	Interconnected nodes representing the actors.
v_k	Peer capacity utilization indicator.
w	The dual function.
$W(.)$	Energy generation/demand welfare.
X, Y	Sets of actors/nodes in G.
x_i	The power generation of prosumer n_i.
x_i^{max}	Upper bound of power generation of prosumer n_i.
x_i^{min}	Lower bound of power generation of prosumer n_i.
$x_{i,j}$	Total traffic flow on link (i,j).
$x_{ij,k}$	The flow of commodity k on link (i,j).

Chapter 1

Introduction

THE current transition of the electric power infrastructure to sustainable and efficient systems is redefining the roles of stakeholders within the energy value chain. In particular, the proliferation of distributed energy resources (DER) has accelerated the development of a community grid where a small-scale local production of energy at the household level [1], harnesses DER to form another layer of the energy network [2] within the consumer domain. This phenomenon, in effect balances the power requirement, minimises energy losses and reduces electricity costs. In a bid to further reduce the carbon footprint, and dependency on the main grid, local generation, consumption and trading of energy are encouraged. Such characteristics empower traditional consumers [3][4] to become proactive prosumers[1] who consume, share, exchange [5][6] or trade unused or flexibly generated energy; and therefore actively participate in the growing energy sharing economy [7].

However, the integration of these independent and distributed prosumers into the grid has brought new challenges in energy coordination and control [8][9][10]. For instance, prosumers mostly rely on renewable sources which are intermittent in nature, with unpredictable energy generation capacity that can destabilise the network. This introduces challenges to conventional plants which need to ramp up quickly when renewable contribution fall below an acceptable level [11]. In a bid to alleviate these coordination challenges, some centralised approaches have been discussed in the literature, for instance [12][13], that require a single entity to assess the whole system and make decisions for other peers in the network. Centralised approaches may be successful in a small-sized network, but are prone to a single point of failure (SPoF), high overhead costs and

[1]Prosumers are producers and consumers of energy.

non-proactive measures in the presence of fault or general performance limitations like limited flexibility and scalability [14]–[16] in a large-scale system. As a result, a distributed energy management and control scheme has gained attention in the literature [16][17][18][19][20]. While these proposed distributed algorithms solves the SPoF of centralised approaches, the authors mostly assumed the underlying communication links is perfect, thus impact of communication constraints is neglected. Hence, this thesis contributes to the growing effort in distributed coordination algorithms over imperfect communication links and platform development for prosumer interactions to foster peer-to-peer energy trading and sharing (P2P-ETS).

1.1 Research Motivation

As the world's population increases, so does the demand for energy, which is estimated to increase by 40% by 2040 [7], with electricity demands growing four times faster than all other fuels [21]. Depending solely on the utility companies to meet the projected increase would result in unreliability of electricity supply. For instance, the recent Venezuela power infrastructure outage that left the whole country in total darkness for days resulting in loss of lives [22] could have been averted if other sources of energy[2] production had been considered. In particular, if energy consumers are taking an active role in the community by producing and sharing energy to other consumers in real time, this would not only benefit the end users but also the community as a whole. Indicative advantages include reducing the transmission losses as energy would be utilised in close-proximity to where it is generated, eliminating SPoF of the utility companies and the potential of profit maximisation, cost and energy savings for the prosumers [9].

To realise these benefits from community energy trading, the uncertain generation output of prosumers, increasingly being connected to the edge of the grid requires an effective distributed energy monitoring and control. This is because each prosumer can make independent decisions to pursue their own 'selfish' and 'altruistic' goals[3], resulting in unprecedented

[2]electrical energy and energy is used interchangeably throughout this thesis.

[3]for instance, to generate more revenue/profit, support charity work, increase reputation, etc.

complexity[4] and uncertainty which renders the centralised control, dispatch and scheduling techniques no longer fit for purpose [23][24][25][26].

Effective distributed energy monitoring, coordination and control could alleviate these challenges for a more reliable integration of DER into the energy grid [23][16][17]. Therefore, developing a P2P-ETS underpinned by distributed algorithms has become an emerging area that motivates this research. This thesis contributes to modeling distributed algorithms, to enable discovery of prosumers, seamless information exchange, energy transfer, transaction management, as well as incentivising prosumers to participate in P2P-ETS by enabling profit maximisation and cost savings. Other motivational constraints include the willingness to trade flexible energy in real time considering prosumers' preferences (price, quantity, distance metrics[5]), generation capacities and energy storage systems.

1.2 Research Aim

This research aims to develop distributed algorithms for P2P-ETS platform for prosumers to actively buy/sell/share energy among themselves in real time considering their preferences (price, quantity, distance metrics), generation capacities and willingness to trade energy.

1.3 Research Objectives

In developing the P2P-ETS platform, three main challenges are identified; how to locate or discover energy trading peers; how to route information among the prosumers; and how to transfer energy among them including maximising their resources and utilities. Thus, the aim of this thesis will be achieved by the these objectives:

1. requirement gathering: to conduct a comprehensive research on state-of-the-art P2P-ETS concepts, technologies and frameworks, their role in energy trading and communication requirements (throughput, latency, reliability and security) as stipulated by IEEE 1547.3-2007 for integrating DER/MG into smart grid. This is useful in understanding

[4] large influx of prosumers in diverse locations with unpredictable energy generation capacity.

[5] local consumption to minimise energy transmission loss

how the various components integrate and to propose a P2P-ETS architecture based on their functions;

2. algorithm development: these objectives are highlighted utilising the proposed architecture stated in (1) to solve the three main identified challenges :

    (a) to investigate and develop a slime mould inspired distributed algorithm to facilitate discovery, path optimisation and energy demand matching between the prosumers on the P2P-ETS platform;

    (b) to investigate multi-commodity flow optimisation and develop a distributed routing algorithm for information dissemination among the connected prosumers on the P2P-ETS platform;

    (c) to investigate gradient-descent update together with multi-commodity flow optimisation and develop a distributed algorithm for energy dispatch, resource allocation and utility maximisation of the prosumers on the P2P-ETS platform.

3. developing the P2P-ETS platform: the methods from (2) will be utilised in developing the P2P-ETS platform. The platform will be demonstrated utilising several connected devices representing smart meters of prosumers for energy trading, while assessing their potential for cost savings.

1.4 Key Contributions

The key contributions of this thesis are summarised as follows:

1. a four-layer system architecture is proposed for P2P-ETS derived from the service oriented network architecture (SONA) and the Smart Grid Architecture model. The system architecture is proposed to categorise the interactions of the key elements and technologies in P2P-ETS based on their functions. This further led to the proposal of a P2P-ETS platform algorithm for distributed energy transaction and management. The research reported in this thesis is carried out on the basis of this architecture as well as the P2P-ETS platform algorithm developed within the research earlier reported in [9];

2. a slime mould-inspired approach to energy network for optimised path between trading peers on the P2P-ETS platform is proposed. The slime mould solution is further extended to maximum flow capacity in distribution networks and energy demand matching between prosumers based on a least-cost distance metrics. The solutions presented therein can be used for congestion control on distribution links, provide alternate paths in cases of disruption on the optimal path and pairing of prosumers to implement local energy consumption and trading [27];

3. a distributed adaptive primal (DAP) routing algorithm is developed to facilitate communication and coordination among prosumers over imperfect communication network links. The algorithm minimises both the communication delay and loss of energy transaction messages that may result due to sub-optimal network conditions. Taking into account realistic constraints relating to network delay and communication link capacity between the peers, the DAP routing algorithm is used to evaluate network performance using various figures of merit such as probability of signal loss, message delay, congestion and different network topologies. The results show that the proposed routing algorithm is robust to packet loss on the communication links with a 20% reduction in delay compared with hop-by-hop adaptive link state routing algorithm. This contribution is reported in [11];

4. a distributed dual-gradient (DDG) algorithm is developed to solve the economic dispatch problem and minimise the energy generation cost whilst ensuring that total generated energy satisfies the total energy demand in the network. The performance of the DDG algorithm is evaluated based on realistic network conditions relating to time-varying network delay and lossy communication links. The proposed solution is extended to realise the global utility maximisation among market-based participants to improve overall costs and maintain fairness of all generators and demands. Results suggest that traders with higher willingness to trade energy achieve higher utility. In addition, the results show reduction in quantity demanded when supply is at the highest price, but the price paid is dependent on the ratio of producers to consumers in the network. [28];

5. a market-based negotiation P2P-ETS platform for prosumers

interaction and energy trading is developed. Utilising the developed matching algorithm, consumers are paired with producers based on their preferences. After the initial matching, the pairs demonstrate autonomy by negotiating with their paired partners the terms of the transactions in a P2P fashion. If an agreement is reached, the pairs exit the market, else, they proceed to the next round with new partners. The performance of the platform is evaluated for local energy consumption. The results showed that consumers of local energy consumption acquired more cost savings of 45% than prosumers that do not trade energy locally. In addition, the degree of the cost savings is dependent on the demography of participants on the P2P-ETS platform [29].

1.5 Thesis Organisation

The remaining parts of the thesis are organised as follows. Chapter 2 provides an introduction to ETS concept, microgrid applications and P2P-ETS architecture. It discusses the motivational factors and enabling technologies for P2P-ETS, and concludes with the prospect of P2P-ETS as well as a proposal of four-layer system architecture for P2P-ETS. In Chapter 3, a slime mould-inspired locality algorithm for peers' discovery and matching consumer energy demand to a producer supply is discussed in detail with the performance evaluation of the developed algorithm. In Chapter 4, the developed distributed data routing algorithm for prosumers is discussed, and its performance evaluation is given. Chapter 5 proceeds to discuss distributed dual-gradient algorithm for optimal dispatch of energy. Multicommodity flow optimisation is adopted both in Chapters 4 and 5, which enables the research to benefit from considering the imperfect communication links. Chapter 6 presents the last part of the thesis, with discussion on the developed P2P-ETS platform utilising the algorithms developed in the previous chapters. A proof-of-concept implementation utilising devices to demonstrate prosumers interactions on the developed platforms in real-time is presented with a case of local energy consumption. In Chapter 7, the main conclusions of the various pieces of work in this thesis are discussed, including recommendations and a future outlook.

The thematic organisation of this thesis is presented in Fig. 1.1. It should be noted that Chapters 3, 4, and 5 addresses different distributed algorithms for discovering peers, routing information and energy transfer among the prosumers respectively using different methods, while Chapter 6 combines the methods of the discussed algorithms to implement the P2P-ETS platform.

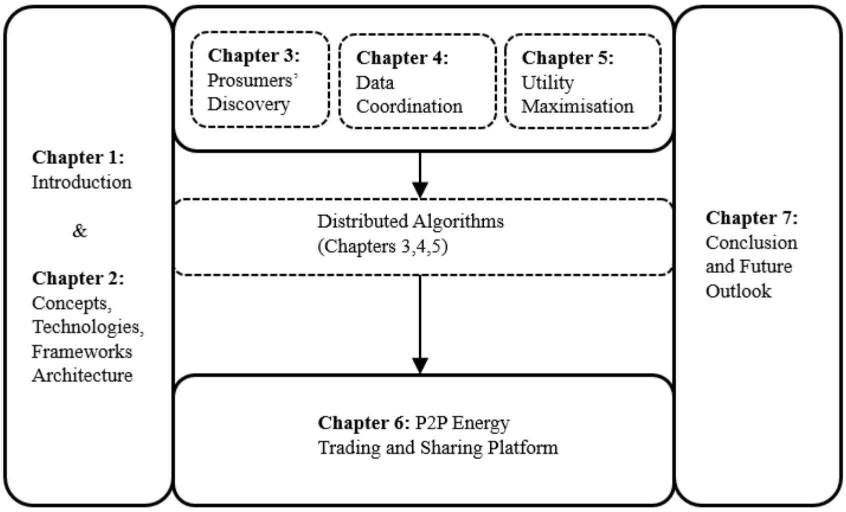

FIGURE 1.1: Thematic Organisation of the Thesis

1.6 List of Publications

Journal Papers

1. **Jogunola, O.**, Adebisi, B., Anoh, K., Ikpehai, A., Hammoudeh, M., Harris, G., & Gacanin, H. "Distributed adaptive primal algorithm for P2P-ETS over unreliable communication links" Energies, 11(9), 2331, 2018.

2. **Jogunola, O.**, Ikpehai, A., Anoh, K., Adebisi, B., Hammoudeh, M., Son, S. Y., & Harris, G. "State-of-the-art and prospects for peer-to-peer transaction-based energy system", Energies, 10(12), 2106, 2017.

3. **Jogunola, O.**, Ikpehai, A., Anoh, K., Adebisi, B., Hammoudeh, M., Gacanin, H., & Harris, G. "Comparative analysis of P2P architectures for energy trading and sharing", Energies, 11(1), 62, 2017.

Conference Papers

1. **Jogunola, O.**, Adebisi, B., Anoh, K., Ikpehai, A., & Hammoudeh, M. "Adaptive distributed algorithm for information management in microgrids in smart grids", IFAC workshop on control for smart grid, Jeju Island, South Korea, June 10-12, 2019.
2. **Jogunola, O.**, Hammoudeh, M., Adebisi, B., & Anoh, K. (2019). "Demonstrating Blockchain-enabled Peer-to-peer Energy Trading and Sharing", IEEE Canadian Conference on Electrical & Computer Engineering, Edmonton, Canada, May 5-8, 2019.
3. Anoh, K., Ikpehai, A., Bajovic, D., **Jogunola, O.**, Adebisi, B., Vukobratovic, D., & Hammoudeh, M. "Virtual microgrids: a management concept for peer-to-peer energy trading", 2nd International Conference on Future Networks and Distributed Systems (p. 43). ACM, Amman, Jordan, June 26-27, 2018.
4. Anoh, K., Adebisi, B., **Jogunola, O.**, & Hammoudeh, M. Cooperative hybrid wireless-powerline channel transmission for peer-to-peer energy trading and sharing system. In Proceedings of the International Conference on Future Networks and Distributed Systems (p. 7). ACM, Cambridge, UK, July 2017.

Submitted Journal Papers (Under review)

1. **Jogunola, O.**, Hammoudeh, M., Adebisi, B., & Anoh, K. "Exploring Blockchain Platforms for Peer-to-peer Energy Trading", CJECE Canadian Journal on Electrical & Computer Engineering, 2019.
2. **Jogunola, O.**, Adebisi, B., Anoh, K., Ikpehai, A., Hammoudeh, M., & Harris, G. (2019). "Multi-commodity Optimisation of Peer-to-Peer Energy Trading Resources in Smart Grid.", IEEE System Journal, 2020.
3. **Jogunola, O.**, Wang, W. & Adebisi, B. "Slime mould-inspired path optimisation and prosumers matching algorithm in Peer-to-Peer energy trading", IEEE Access, 2020.
4. **Jogunola, O.**, Tsado, Y. & Adebisi, B. "Peer-to-Peer energy trading platform: a case of local energy consumption", IEEE J. Modern Power Syst. and Clean Energy, 2020.

Chapter 2

Energy Trading Concepts, Technologies and Frameworks

THERE is an increasing variety of motives driving the power industry. In the UK for example, this drive for competition was accelerated in 1988 when the British government announced plans to privatise the electricity supply in England and Wales [30]. Thereafter, the Nordic electricity market (comprised of Sweden, Finland and Denmark) and US followed. This suggests that regulators in different jurisdictions forecast that new values could be created by liberalising electricity generation and supply. In these and other markets, the optimal price (the marginal cost of generation, when there is no risk of rationing) largely depends on the bidding behaviour in the wholesale market [30]. Until recently, energy trading has been a wholesale business, mostly among big corporations. However, recent advancements in the use of DER have inspired the trials of small and medium-scale P2P-ETS in different parts of the globe such as The Netherlands [31], sonnenCommunity in Germany [32], Piclo in the UK [33]. and Energy Internet in China [34]. Additionally, some energy traders are inspired by blockchains including EnerChain [35] in Europe and Brooklyn P2P energy trade [36]. Bilateral[1] energy transactions between prosumers will not only help to better harness the output of distributed generation systems [38], but also promote effective energy management at the edge of the network.

Adapting the structure earlier reported in [9], this Chapter on ETS concept discusses the three coverage areas shown in Figure 2.1. Section 2.1 discusses the motivational factors including cost optimisation and environmental

[1]A bilateral contract in an electricity market is an agreement between a willing buyer and a willing seller to exchange electricity, rights to generating capacity, or a related product under mutually agreeable terms for a specified period of time [37].

benefits. The enabling technologies that could foster P2P-ETS are discussed in Section 2.2, covering the microgrid (MG)[2], energy storage systems and ICT. Section 2.3 discusses the required framework, starting from energy trading structure, operation mechanism and optimisation techniques. Section 2.4 discusses grid constraints and network visibility, while Section 2.5 highlights the prospect of P2P-ETS and the proposed architecture is presented in Section 2.6. Section 2.7 presents the identified challenges to P2P-ETS, Section 2.8 provides an overview of the methodology used in the thesis, while, the conclusion and summary of the chapter is presented in Section 2.9.

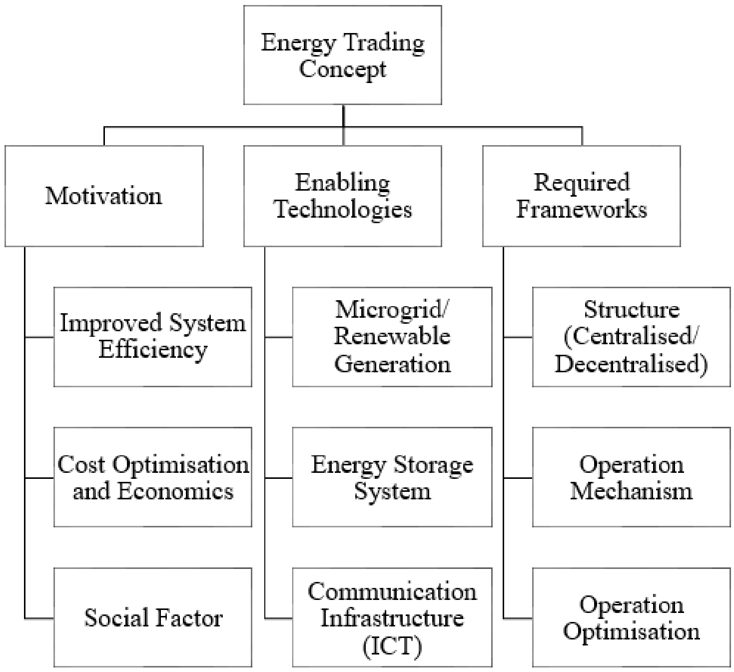

FIGURE 2.1: Overview of the energy trading concept [9].

2.1 Motivational Factors for P2P-ETS

To trade, share or buy energy, various 'actors' are involved in the exchange process in addition to prosumers that supply and consume energy [39]–[41]. These actors include a trader or local-grid operator that buys energy to trade at a margin [42]–[44], a producer that generates energy for sale in large quantities and consumers that rely on those media to meet their energy demand. The actors are equipped with smart meters which record details of

[2]MG refer to a standalone system comprising of energy generation resources, connected loads and storage system. Refer to Fig. 2.3.

their energy profiles and facilitate bidirectional communication during ETS. An example of actors interaction with a trading platform is shown in Fig. 2.2, from distributed system operators (DSOs), to federated power plant (FPP)[3], and to consumers. While these different actors are connected to transact energy, there are different motivational factors and benefits prompting their decisions to trade energy. This section discuss these factors:

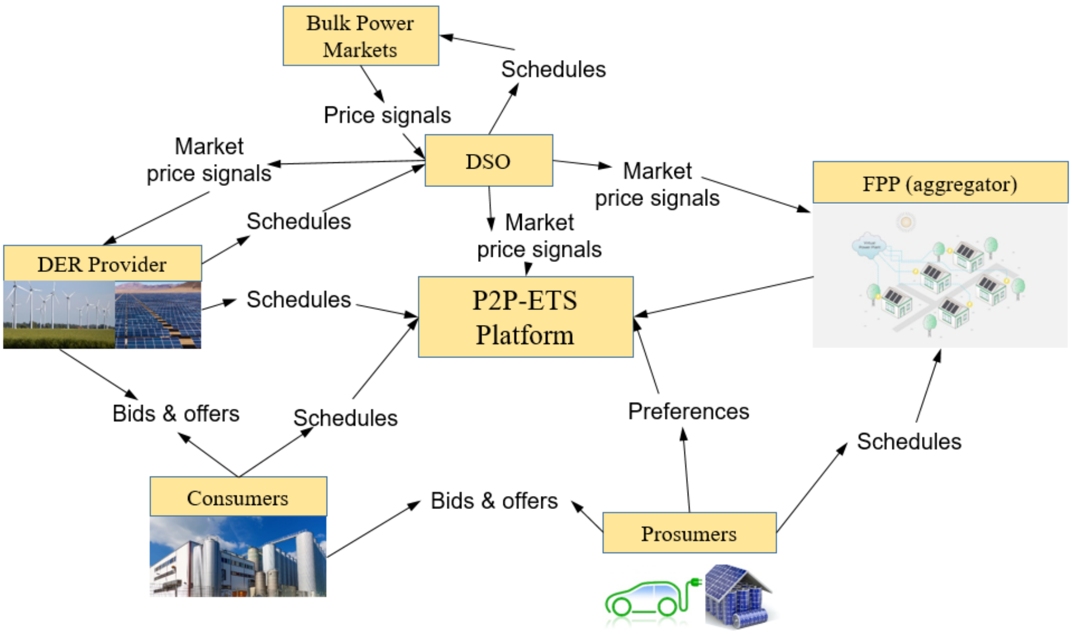

FIGURE 2.2: Actors interactions with the P2P-ETS Platform [9].

2.1.1 Improved Network Agility

P2P-ETS is hugely motivated by the need to manage a complex energy system consisting of numerous distributed and self-controlled energy producers and load resources. Those controllable and flexible resources, either on the supply side or demand side, are incentivised to transact with those non-controllable and variable ones [46]. With this in mind, P2P-ETS optimises the use of DER at the community level to reduce the dependency on the main grid by creating a platform for the distributed units to transact energy. Integrating more locally sourced energy improves the power system efficiency, reliability and opportunity to supply energy to remote locations. In addition, utilising these DER, P2P-ETS reduces the requirements for

[3]FPP concept is a virtual power plant (aggregator) formed through P2P transactions between self-organising prosumers to addresses social, institutional and economic issues of virtual power plants, while unlocking additional value for P2P energy trading [45].

DSOs to address energy generation/load uncertainties by creating a fair and transparent platform that allows all resources to transact energy thereby balancing the intermittent supply and variability in demand [9][46]. Thus, P2P-ETS has shown potential to improve the power network agility by increasing its reliability and efficiency as well as the opportunity for DSOs to also provide reliable energy supply using the platform.

2.1.2 Improved System Efficiency

A sustained growth in adoption of ETS can effectively improve network efficiency [47], because the integration of DER and ESSs into the power grid balances the supply and demand of energy as discussed. This enables the utility companies to provide other ancillary services, thereby improving the power grid efficiency. Moreover, with the integration of P2P-ETS, consumers' demand will be met locally, meaning the use of distant high capacity generator options, and congestions on transmission lines will have the tendency to decrease; reducing system operational costs [46]. For instance, utility companies dispatch more generators to meet the growing demand of consumers in peak periods; however, with P2P-ETS, the demand ratio reduces during peak periods, thus relieving the utilities of the additional cost and effort to meet peak demand. These improvements will enhance the reliability of the equipment and reduce the average customer interruption costs [7] thereby benefiting the whole of the grid in the long run. The improved system efficiency is realised by utilising the P2P-ETS to sell/buy excess generation at the MG level during the peak hours. To further improve energy efficiencies, significant amounts of heat waste from power generation sites can be utilised for heating and cooling of buildings, refrigeration through absorption chilling, and heating domestic water [7].

2.1.3 Cost Optimisation and Economics

According to [48], one of the promises of power grid modernisation is the possibility to optimally deploy DER for the benefit of asset owners. From the perspective of prosumers, cost optimisation is widely reported as a major motivation for bilateral P2P-ETS [49]–[55]. Cost optimisation can be achieved through reductions in energy generation costs, transportation costs, energy demand flexibility, minimised energy losses, or prosumers' utility and profit maximisation [56]. Interestingly, a breakdown of an electricity bill reported by Ofgem [57], showed that 33.52% of a bill/kWh is the real energy usage cost, the remaining 66.48% are service charges including network cost (transmission, distribution and balancing), supplier operating costs, VAT, etc. Thus, with P2P-ETS in the community, the network cost due to transportation and other associated costs can be reduced. For instance, households with installed solar panels in the UK are paid 5.38p [58] for every kWh of solar electricity which they sell to the grid under the export feed-in-tariff scheme. Meanwhile, a normal household pays an average of 14.3p/kWh to buy electricity from an energy retailer or DSO. With P2P-ETS, they can both potentially optimise their costs, e.g. buying and selling for an average of 11p/kWh, including transmission and distribution fees, thereby making a profit as well as paying less on their electricity bill. According to Ofgem [59], this type of system of offloading the peak demand and selling energy within a community would save consumers £17bn−£40bn by 2050.

2.1.4 Environmental Benefits

Global carbon footprint has made countries around the globe to set targets for reducing their greenhouse gas emissions (GHE) in the next decade. For instance, in the UK, the Government has set to bring all GHE to net zero by 2050, compared with the previous target of at least 80% reduction from 1990 levels [60], this means the environment benefits of P2P-ETS are a major drive towards its successful development. The full exploitation of renewable and distributed energy generation is a critical element in reducing GHE. With renewable generation, energy is used up at or close to the point of production, which drastically reduces distance-related transmission losses thereby decreasing the GHE [9] and its related aftermath due to air pollution, including respiratory (cardio) health related issues. In addition, according to 'UK energy in brief' 2019 publication, 28.9% of energy consumption and 14.5% of CO_2 are mainly generated by residential buildings [61], thus, a working P2P-ETS would collectively reduce the household carbon-footprint [62] as well as offload some of the energy consumption off the grid for improved efficiency and environmental benefits. By utilising a platform to trade energy within the community, it is shown in [63] to reduce the carbon emissions by 12% by year 2030.

2.1.5 Social Factor

Excess flexible energy produced can be shared, traded or freely supplied to another consumer in need. Currently, 2.53 *million* households live in fuel poverty[4] in England [61], that is estimated to be more than one in ten households. Meanwhile, P2P-ETS equipped prosumers with an expanded flexibility and choice in deciding how to use their excess produced energy (to trade, share, gift) and in choosing who to share the energy with, including the quantity of energy to trade without a maximum limit as opposed to net-metering[5]. Thus, by delivering energy as a resource that can be given away as a social capital by individuals to a target party, the values derived from such gestures can be used as a strategic tool to promote social cohesion, reduce fuel poverty and improve the sense of community [9].

2.2 Enabling Technologies

To participate in P2P-ETS, a prosumer should be able to either generate, consume or be willing to trade or share energy. Enabling technologies are the infrastructures that enable energy production, storage and trading among prosumers. They are broadly categorised into MGs; DER, ESSs, and an ICT to enable communication and interaction among the various sub-systems and the prosumers. This section discusses the MG including DER, and ESSs, and the communication technologies in MG.

2.2.1 Microgrid and its Applications

A MG is a small-scale power network consisting of ESS, DER and loads that act as a single controllable entity with capability to provide electricity to a small community or household using its own renewable sources. In most cases, MG can act as an energy prosumer [9]. MG are distributed with close proximity to where energy is produced and used and not necessarily dependant on the power grid, meaning it can be operated in an isolated

[4]a household is fuel poor if their fuel costs are above national average; and when they pay the amount, their residual income would be below the poverty line [61].

[5]Net metering is a billing mechanism that credits PV owners for the energy they add to the grid. This should be economically attractive to the PV owners, however, it is not because the grid usually put a cap/limit to what can be supplied for control purposes, and the return is always minimal.

mode. This control ensures continuous energy availability with or without the main grid. An example of MG with interconnection of DER, ESS and connected loads is illustrated in Figure 2.3.

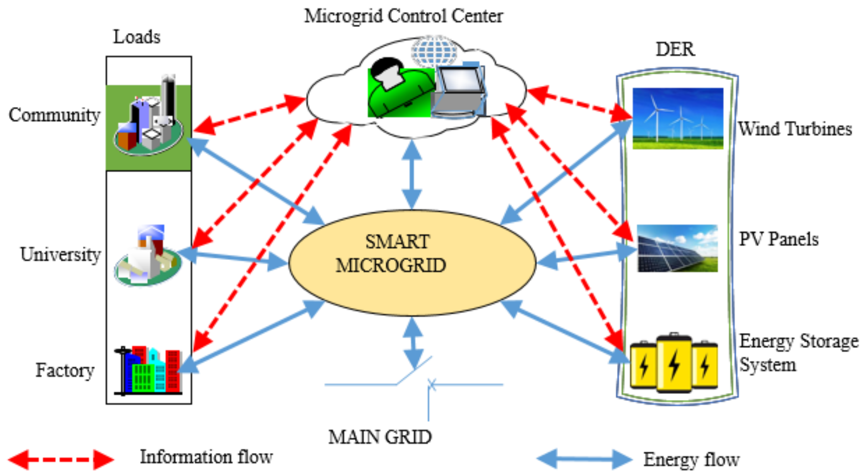

FIGURE 2.3: Components of a microgrid [64] showing both energy and information flows.

While MGs are an attractive technology for P2P-ETS, the MG subsystem/applications are what enables MG to function effectively, thus, to investigate the operation of P2P-ETS, it is necessary to start from the MG level by deriving the characteristics of its subsystems/applications. The highlighted MG applications are examined for their diverse network requirements due to their impact on P2P-ETS;

- Meter data management system (MDMS): The smart meter device is located at the Customer Premises Network (CPN) and used to measure and record customer energy consumption as well as power flow from DER, loads and ESSs in a predefined intervals [65]. The measured quantities are sent either on-demand or periodically to the utility grid for billing purposes and grid management. Increase in metering data due to the two-way communication between the customer premises and the utility company, makes meter data management a critical application to consider. MDMS has the responsibility to collect, store, analyse and process the data for appropriate pricing or billing, demand response programs, better customer experience and energy consumption management services. MDMSs have the capability to manage other meter types including electric, heat, and gas, by turning it on and off and transmitting data when appropriate [48][66][67]. In addition, home energy management systems consisting of a smart meter and customer appliances, monitor and control these appliances to optimise local energy production, consumption or storage [48].

- Demand Response (DR): It operates within the CPN to interact with the service providers. DR is used to manage the energy delivered to consumers to balance the grid's supply and the consumer's energy demands during peak periods. DR provides opportunity to better utilise the available energy for more reliable and cheaper operation of the grid [66]. It is designed to influence the energy consumption patterns of a customer using a range of programs like dynamic pricing. DR programs could also be incentive-based including gamification of energy, direct load curtailment, demand bidding and buyback, and emergency demand reduction or price-based programs [66]. Examples of price based DR programs include Time-of-Use (TOU), Critical Peak Pricing (CPP), Real-Time Pricing (RTP) and Inclining Block Rate (IBR) [67][68]. DR incentivise some ways to add flexibility to the energy market, where a producer participating in DR program can change their consumption approach by subscribing to the time of use DR program. Such a program could enable the producer to submit a bid to the energy market to sell the excess/flexible energy realised through the DR program. For many producers, this could take place daily, resulting in increased profit for the producer;

- Asset Management: This is an application designed to ensure quality of service for customers at a minimum cost. It offers integrated management, optimisation of the work order process, automation and scheduling processes. Some of the key indicators that can be balanced by asset management include the assets (smart meters, home energy management systems, ESSs, DER, appliances, etc.), system performance, maintenance costs, failure risks and reliability through the use of a communication infrastructure [66]. With asset management, system fault and resulting downtime would be dealt with as it occurred for optimum efficiency of other applications depending on it, for example, energy trading.

The discussed MG applications have direct impact on P2P-ETS, for instance, a smart meter provides the interface to communicate with other prosumers, MDMS and HEMS, provides other ancillary quality of service (QoS), while

DR encourages flexibility of energy usage for cost savings and increased profits on the energy market.

2.2.2 Energy Storage Systems

Apart from DER, ESSs are considered an essential element in balancing micro-generation of energy from renewable resources [69]. ESSs are an ideal way to support energy generation, by offering their capability to store unused or excess energy and later discharge the energy when required. They offer flexibility during periods of high intermittent and fluctuating energy production. The energy system technology can therefore support the grid reliability and electricity supply. The importance of ESS has been researched in the literature. For instance, study [69] argues that the users with storage systems are able to reduce their monetary expenses to a greater extent than consumers without storage systems. In addition, the authors in [70] highlighted the importance of ESS in shaving peak energy demands and filling valleys in system loads. After the initial investment cost of acquiring the ESS, the storage system has potential of reducing the subsequent energy cost by charging during off-peak period when energy is cheapest and discharging during peak period when energy is more expensive. ESS can be located at the customer premises as well as at the utility network to complement energy generation from the power grid by smoothing out power fluctuations. Also, ESSs can be used to increase system reliability and power delivery capacity. In P2P-ETS, energy produced in excess of the current real-time requirements usage is stored in an ESS for exchange with other prosumer at a later time, thus, ESSs are no doubt an important enabling technology for P2P-ETS.

2.2.2.1 Electric Vehicle (EV) charging

The introduction of EVs into the grid is becoming more significant in the development of sustainable energy solutions. EV(s) have the capability for storage using their rechargeable battery pack to operate the vehicle's electric motors. EVs can also be an example of a distributed storage system to supply the customer premise's grid with power through their charged battery. EVs interact with the grid in two modes: Vehicle–to-Grid (V2G), and Grid-to-Vehicle (G2V). Depleted batteries of the EVs are charged in G2V mode, and the EVs supply energy to the grid through its charged batteries in V2G mode [66][71]. The incorporation of EVs into the grid is currently an area of significant interest, with a specific focus on battery charging times which are currently long, and a major barrier. An additional focus is the deterioration of battery's ability to retain charge with the number of charging cycles [72]. Thus, research [72] suggests that charging the EV battery with constant current and voltage could reduce the EV charging time by 16% and extend battery life by 10%. EVs are in uptake and their participation in P2P-ETS is an active research area; for instance, [73][74] investigated enabling localised P2P trading with EVs to reduce the impact of the charging process and to incentivise the discharging of EVs to balance energy demands. This research concluded that the system is economically beneficial to all the parties involved with a potential of reducing energy costs for drivers participating in the P2P-ETS by up to 71%.

2.2.3 Information Communication Technologies

The third enabling technology for P2P-ETS is the communication infrastructure. Communication is essential in MG to facilitate bi-directional information exchange needed for the MG coordination. The presence of a communication system also helps the system operator to pro-actively detect anomalies before they result in disruptions or outages by making system-level information accessible. Communication infrastructure incorporates protocols, networks and technologies that enable the distribution of measurements and commands within the power system and subsystems [75] supporting P2P-ETS. The MG ICT infrastructure needs to be reliable, scalable, secure, available and easy to manage.

Communication among MG applications is as vital as communication between prosumers trading and sharing energy. Energy data generated by each application is required to be communicated to the appropriate endpoint for maximum efficiency of the whole system. There are three levels of bidirectional communication in a typical MG. The lower level communication is between the energy production and usage infrastructure, i.e. loads, DER, etc.; the second level is the communication with the MG control center, which controls all the application components; the final level is that of the MG communicating with other MGs in the neighborhood [23] for possible P2P-ETS. This communication hierarchy is depicted in Figure 2.4.

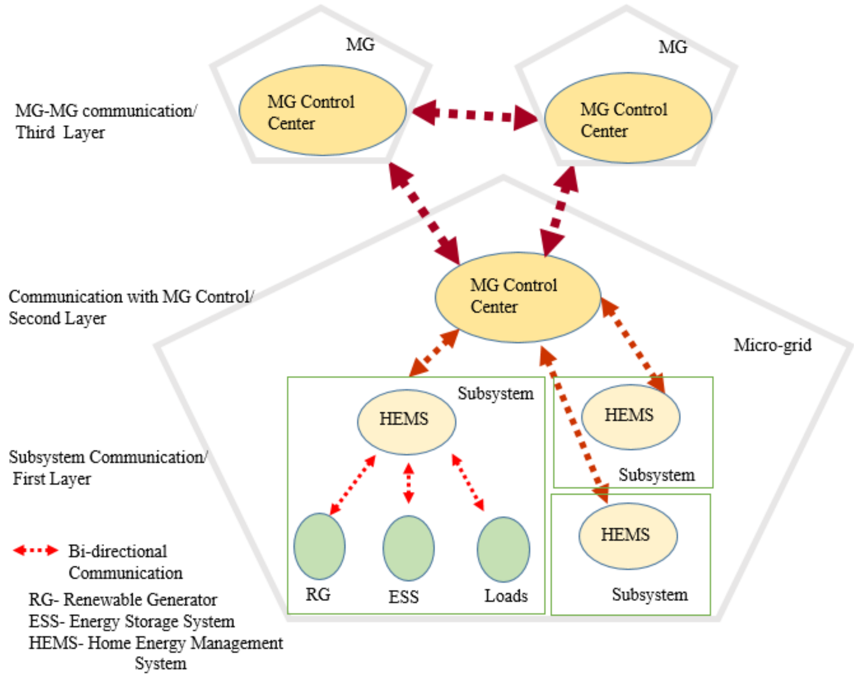

FIGURE 2.4: Hierarchical communication layers in micro-grid (MG) [23]

2.2.3.1 Communication Technologies in the Microgrid

Feasible communication technologies in MGs include wireless and wireline technologies. The rest of this section provides a summary of the communication technologies that can be adopted for control and communication in MG applications [9][64][67][68][71][76][77].

- Power line communication (PLC): PLC is the transmission of data over electric power cables, thus enabling utility companies to utilise a single infrastructure for data and power transmission. Since PLC operates on already established power line infrastructure, the cost of deployment is low, and it has been proposed for grid communication in the literature [76]. However, grid communication over PLC will experience the same challenges faced by power cables such as signal attenuation and electromagnetic interference [76]. PLC can be categorised into three types: broadband PLC (BB-PLC), narrowband PLC (NB-PLC) and ultra-narrowband PLC (UNB-PLC). The NB-PLC data rates can range from 1 bps up to 500 Kbps, and it can cover a distance of about 150 km, while BB-PLC has higher bandwidth performance, but shorter coverage, up to 200 Mbps over a few tens of meters and about 10 Mbps over 8 km. Thus, BB-PLC is commonly found in home area network (HAN) applications such as home automation. The UNB-PLCs operate within 125 Hz and 3 kHz, supporting data transmissions coverage of up to 150 km with data rates of one bits/s to tens of bits/s [78]. Specific applications where PLC has been employed in MGs are in EV charging and distributed generation systems [79]. The EV direct current charging uses PLC to manage communication between the vehicle and the charging post, employing the combined charging system specification standard, while NB-PLC technologies are seen as a good alternative for distributed energy generation [79];

- Optical fibre: Data is transmitted over optical fibre through pulses of light. Optical fibre has a low interference and attenuation rate, which makes it suitable for long distance communication. Optic fibre communication has a coverage range of 62 miles before signal regeneration is required, also it provides a total bandwidth in the order of Gbps (155Mbps-2.5Gbps for up to 60km and 10-40Gbps for up to 100km coverage range) [67]. An optical fibre communication network is characterised by low latency, high data rate, reliability and immunity to electromagnetic interference. Suitable areas of deployment in MG are neighbourhood area networks (NAN), backhaul networks and wide area networks (WAN). Specifically in demand response, meter reading and distribution automation. Its main drawbacks are the high cost of installation and maintenance [67].

- Digital subscriber line (DSL): DSL transmits digital data over telephone lines. Thus, the cost of deployment is low because the infrastructure is already in place. However, the electricity utilities pay a service charge to the telecommunication operators to maintain the communication network infrastructure within the power network [71]. Typical data rate and coverage distance of DSL varies dependant upon the specification that is applied. For example, the asymmetric DSL, data rate ranges from 8–24 Mbps for downlink and 1.3–3.3 Mbps for uplink, covering a distance of 4–7 km [71]. Furthermore, the data rate of very-high-data rate DSL ranges from 52–85 Mbps for downlink and 16–85 Mbps for uplink, covering a distance of 300 m–1.2 km. DSL provides high throughput with reduced latency; hence, it is found to be applicable in MG applications like demand response and smart metering [67];

- Wireless personal area network (WPAN): WPAN is based on the IEEE 802.15x series of standards. They are designed for information exchange over short distances to address a low to medium data rate for personal computer networks and local area networks (LANs). ZigBee/6LowPAN and Bluetooth technology are examples of WPAN. WPAN generally has a low coverage area and data rate. The ZigBee/6LowPAN coverage range is up to 70 m with the data rate ranging from 20–250 kbps, while the Bluetooth coverage range is up to 10 m with a data rate of 712 Kbps. ZigBee has low power consumption, and it is fully interoperable with IPv6-based networks. WPANs are typically low-cost systems with adequate security for short-range deployments [71]. Some of the major weaknesses of WPANs are low bandwidth/data rate and low coverage area, they do not scale to large networks. Applications of WPAN are found in home automation, home area network (HAN) and smart metering systems that require interaction between sensors and power grid equipment with a low data rate over a short distance [64];

- Wi-Fi: This is based on the IEEE 802.11x family of standards to support point-to-point and point-to-multipoint communication. Wi-Fi can provide a data rate of up to 11 Mbps with the highest standard in the series, 802.11n, providing a maximum data rate of 600 Mbps [80]. The goal of the IEEE 802.11x series is to replace cable/wired networks by offering high network flexibility and low installation cost. However, it has a very limited range, and it is subject to high interference given that it mostly operates in the industrial, scientific, and medical radio band. Thus, the IEEE 802.11x series can be useful in MG where the signal interference and data coverage range are low, such as in distribution automation, monitoring and control of DER and customer premises networks, for example, HANs [64][68][76], including applications in DR programs [67] and EVs when interacting with HANs [80];

- Worldwide Interoperability for Microwave Access (WiMAX): WiMAX technology is standardised in IEEE 802.16x. The major motivation for WiMAX is to provide last mile broadband wireless access as a substitute to DSL and cable services. WiMAX provides a wider coverage area compared with Wi-Fi, it supports mobility and multiple users simultaneously and offers reliability of service [80]. WiMAX can provide a data rate of up to 70 Mbps with the highest standard in the series, 802.16m, providing a maximum data rate of 1 Gbps for a fixed network and 100 Mbps for a mobile network. Major drawbacks in using WiMAX are the high cost of ownership, high amount of terminal equipment and complex network management [80]. In MG, WiMAX is applicable in short and long distance communication like in mobile workforce management and backhaul communication technology. WiMAX is also applicable in smart metering and in real-time pricing [67][71];

- Third Generation/Fourth Generation (3G/4G): Cellular networks support a wider coverage area compared with other wireless technologies. Thus, they have found application in supervisory control and data acquisition systems in smart grids [71]. The disadvantage of cellular networks are their cost [80] and variability in throughput and latency performance. However, research is ongoing to optimise the performance of cellular networks. Thus, new generations of cellular networks that support higher data rates are being developed. The 'Third Generation Partnership Project industrial standard' developed 3G cellular technologies. 3G technologies can provide a data rate range of 14.4–84 Mbps for downlink and 5.75–22 Mbps for uplink, with a coverage distance of up to 5 km. The successor of 3G is the 4G network, developed for mobile ultra-broadband Internet access supporting a data rate of 362 Mbps–1 Gbps for downlink and 86–500 Mbps for uplink with a coverage distance of up to 100 km [80]. A possible use case in MG communication will be in distribution automation, DR, pricing and smart metering [67]. Also, EV can stay connected to the smart grid when on the move by using public 3G/4G cellular networks [80].

- Fifth Generation (5G): This telecommunication technology is currently being developed with numerous examples of beta test cities worldwide and offers higher capacity than the present 4G technology. The unprecedented increase in connected world and IoT devices including smart meters and sensors, requires that the 5G standard supports data rates of tens of megabits per second, simultaneously for tens of thousands of multiple users [81]. The latency should be significantly reduced as compared to 4G networks, enabling high quality of service (QoS) and quality of experience (QoE) support. 5G has the potential to provide cost effective, increased network stability and scalability, reduced power consumption and more connectivity among devices [81]. The International Telecommunication Union (ITU) established key capabilities for 5G including enhanced Mobile Broadband, ultra-Reliable and Low Latency Communication, and massive Machine Type Communication. Using these capabilities, ITU defines the minimum technical performance requirement for 5G with main KPIs as; peak data range of 20Gbps downlink and 10Gbps uplink, user data rate of 100Mbps downlink and 50Mbps uplink and latency between 1-20ms [82]. Taking this into consideration, the recent roll out of 5G in the UK is expected to feature an average speed of 130Mbps-240Mbps downlink with theoretical speed of 1-10Gbps downlink, with a theoretical approximate latency of 1ms [83]. In terms of MG applications, a key driving sector for evolution of 5G is smart mobility, highly connected EV, for monitoring purposes, using 5G to enable real-time data transmissions [84].

2.2.3.2 Smart-Grid Subsystem Communication Network

Communication networks in MGs connect energy-generating sources, distribution networks and consumer systems to the management system; the MG control centre. In MG communication networks, these are found [67][76].

- Home area networks (HANs): a low bandwidth network providing two-way communication between the customer's home appliances and power equipment such as smart meters [68]. The data exchanged includes voltage, current, power and frequency ratings. This data can be altered in DR and demand side management. Communication technologies found here are ZigBee, Bluetooth and Wi-Fi. Depending on the location of the MGs, the HANs can be industrial area networks if located in an industrial area or building area networks if in a building [67];
- Field area networks (FANs): are two-way communication networks between customer premises and MG control stations, for example,

forwarding data collected in a HAN to a MG control centre. FANs enable monitoring and control of energy distribution networks to foster energy delivery. Communication technologies include Wi-Fi, PLC and WiMAX [67][76];

- Wide area networks (WANs): A WAN network is used when MG is in grid connected mode to the utility grid. This MG mode requires a high bandwidth, two-way communication over a long distance with effective monitoring and sensing capability. Selection of the appropriate communication technology depends on its distance (coverage), cost effectiveness and bandwidth. Some technologies that could be applicable include Wi-Fi, WiMAX, and 3G/4G [67][76].

2.2.3.3 Micro-grid Communication Requirements

To design a communication infrastructure[6] for a MG system, it is necessary to identify the specific application requirements that the communication infrastructure must satisfy. The IEEE 1547.3-2007 standard defines four performance metrics for DER integration into the power grid, which characterise their communication network performance. Table 2.1 shows the various MG applications discussed in Section 2.2.1 and their communication requirements [64][67][68][76]. These performance metrics and their implications on MG applications are as described:

- Latency: This is a measure of time delay interval between transmission and delivery of a message and is stated in seconds. Latency requirements imply the acceptable window of delay associated with data flow from a sending peer to a receiving peer for each energy network application [67]. Latency is a critical factor to consider when designing a communication architecture. Moreover, in energy network applications, energy information exchanges between subsystems have tight deadlines and thus require prompt transmission. Therefore, a communication network for transferring energy related messages should aim to meet latency requirements [76].

[6] Communication infrastructure embodies protocols, networks and technologies that enable the distribution of measurements and commands within the power system and subsystems [75] supporting P2P-ETS.

[7] (MAC + Phy)

[8] (E2E application)

TABLE 2.1: MG applications and communication requirements [23][64][67][68][76]. Table acronyms - MAC: medium access control; DCS: distribution customer storage; Mgt.: management; Auto.: automation.

Application	Latency	Throughput (kbps)	Reliability (%)	Security
DER and Storage	<1 ms–1.5 s[7] 15 s[8]	9.6–56	99–99.9	High
EV Charging	2 s–5 m	9.6–56	99–99.9	High
Smart Meter	Variable	10/m	>98	High
Home Energy Mgt.	300 ms–2 s	9.6–56	>98	High
Demand Response	<1 m	14–100/node	>99.5	High
DCS	<5 s	120–144	>99.5	High
Meter data Mgt.	2 s	56	99	High
Asset Management	2 s	56	99	High
Home Auto.	seconds	4.8–48	>98	High

- Reliability: The communication network must ensure that a message will reach its recipient or target peer as intended and without losses. This is important to ascertain prompt energy distribution and to ensure that energy will be made available when it is required. Therefore, in P2P-ETS networks, unreliable communication among peers can be caused by a number of factors inherent in P2P networks including link/node failure, routing inefficiency, high churn rate of peers, inadequate communication infrastructure, etc [23][85][86]. All of these possible causes should be considered when selecting or designing a communication architecture for energy networks. In addition, different applications require different levels of reliability, thus communication systems should provide flexibility in the choice of reliability based on the application [23].

- Throughput: It is a measure of the amount of data per time interval transferred through a communication channel, which is expressed in data bits per second. With the increase in the amount of data generated from energy network applications, the choice of P2P communication architectures should be able to accommodate these increasing bandwidth applications to ensure low transmission delays, reduce packet losses and ensure prompt peer discovery and message delivery [23][68].

- Security: A secured communication system is needed to ensure that the P2P-ETS network is only accessible to authorised personnel, that system data is not compromised and that it is always available when needed. As a MG is a critical infrastructure requiring stringent resilience to cyber-attacks, this includes ensuring the data privacy of connected prosumers [73][87]. Thus, communication systems must provide assurance that energy assets and the P2P-ETS network are protected from cyber-attacks, customers' data are protected from unauthorised access and that the communication system is robust against network attacks [23].

In general, a well-defined communication mechanism is desired among different MG or actors trading energy to update their energy demand and supply profile, to monitor their energy generation, storage, and consumption data, and to detect early faults in their connected components.

2.3 Frameworks for P2P-ETS

Lastly, after assessing the enabling technologies for P2P-ETS, with discussion of MG, its communication technologies and requirements, this section focuses on the required frameworks. The framework to achieve the desired outcome can be described in terms of structure, operation mechanism and operation optimisation. In this regard, a key question is whether the trading structure should be fully distributed [74][88]–[91] or centralised through a platform/energy market [92]–[95] operation.

2.3.1 Energy Trading Structure

The centralised and decentralised energy trading structures are discussed as follows.

2.3.1.1 Centralised Energy Trading Structure

In a centralised ETS structure, prosumers are not in full control of the sharing and trading process of the energy they generate. Their operation is regulated through an independent central unit [96] a broker [38] or platform. Some authors as found in studies [97] and [98] believe that some form of coordination with control is required to minimise energy loss and for transaction management. Therefore, an energy sharing provider

(ESP) [97] or a cloud based control [98] will be needed to manage prosumer transactions and ensure energy transfer and balancing.

With a price-based DR [97] energy sharing model using an ESP, although the ESP provides some form of coordination and transaction management, a major drawback of this approach is the resulting increase in electricity cost for each participating prosumer and utility company. This is because the ESP purchases electricity from the prosumers and/or utility provider with net power export, then sells to the prosumers and/or the utility provider with some margin. In addition, communication delays can also be an issue, created by the dependence on the ESP.

An example of a centralised system for energy coordination is the federated power plant (FPP).

2.3.1.2 Federated Power Plant

FPP[9] offers a unique way to connect a wide range of distributed energy sources and controllable loads to form an integrated self-healing network of energy resources. Away from traditional electricity infrastructure, FPP represents a paradigm shift in which independent and distributed energy generation and storage assets are integrated to form a network of energy resources logically managed as a "single" plant. The rich diversity of such energy sources and their cooperative mode of operation enable the FPP to reliably deliver energy whenever it is needed. This functionality is in tandem with the sustainability agenda of the smart grid vision. From a utility perspective, these distributed generation components imply that FPP inherently holds some DR capabilities that not only reduce dependence on the main grid during energy shortfalls due to peak demand or maintenance activities, but can also improve network resilience. FPP is particularly suitable for small communities, educational campuses and small-to-mid-sized industrial facilities. The FPP may be equipped with a controller to enforce reactive demand regulation, for example by disconnecting household loads, or connecting to multiple available generation sources to meet the current load of the community according to the aggregate load profiles of the houses [99]. In such cases, the controller determines from which generator company to purchase power based on the

[9]FPP concept is a virtual power plant (aggregator) formed through P2P transactions between self-organising prosumers to addresses social, institutional and economic issues of virtual power plants, while unlocking additional value for P2P energy trading [45].

current shortfall and the price. It is necessary at this point to clarify some common misconceptions about MG and FPP. Whereas the former can be deployed per household to serve local loads within its geographical boundaries, following grid events, the latter pushes those boundaries by interconnecting various assets (including MGs) to form a single network of energy resources. In other words, an MG is made up of at least one energy source and load, while FPP aggregates geographically-dispersed DER of various types and sizes into a single portfolio that can be administered as a single power plant. FPP operators are therefore known as aggregators, FPP and MG can co-exist in a P2P-ETS system.

It follows that the centralised trading structure including a FPP offers some form of coordination and control for the connected components and peers trading energy. However, there are drawbacks to the centralised ETS. Firstly, prosumers do not have autonomy to make decisions by themselves, they have to follow some rules made by the aggregators. Secondly, privacy is a major issue, as prosumers are required to share their energy profile before participating in P2P-ETS. Thirdly, as the network grows, scalability becomes a challenge. Finally, depending on the type of operation on the central platform, a higher fee would be paid either through commission[10] to the platform or through increase in energy price[11]. The challenges posed by the centralised ETS strcuture mean that discussion of the distributed ETS structure are warranted. This is discussed in the next subsection.

2.3.1.3 Distributed Energy Trading Structure

Distributed energy trading encompasses direct interaction among prosumers [100], or EVs [74], utilising some form of time-allotted coordination [101], where directly connected prosumers are neighbouring partners. In some instances when the energy demands are not met by the neighbouring partners, the demand and/or supply will be requested from the utility company [101].

Distributed ETS involves multiple interacting altruistic users interested in optimising their own utilities without necessarily considering other users or grid conditions. To implement a distributed ETS without a central controller, some coordination algorithms or game theory approaches are

[10] a charge on every unit of energy sold or purchased on the platform.
[11] an aggregator buying at a lower amount and seller at an higher price to the consumer.

required to obtain optimal solutions in a decentralised way. This includes an analytical solution to allow MGs to interact in order to optimise cost [49] or minimise the network operation cost [102][88]. In cases involving distributed ETS between EVs, the impact of the charging process on the power system during business hours was reduced [74]. In terms of privacy, each MG only shares its local energy bid with potential sellers, thereby keeping the local cost function and consumption information private.

Of course, interconnecting a MG with the marketplace comes with additional monitoring and control complexities. In this regard, a recent survey on control techniques for MG in [103][104] reported that as MGs become sophisticated, each of them will deliver new energy services that could be of mutual interest among MGs or clusters of MGs. In [93], a description of a marketplace for P2P electricity sharing is presented. This resource-sharing network will enable electricity access in off-grid areas. With the use of power management units, the overall system is less expensive and more scalable than conventional MG, thus providing more affordable and scalable electricity access.

Distributed energy exchange including P2P-ETS provides some optimisation benefits in terms of cost reductions due to energy transportation and direct transactions between neighbours. In addition, it can balance local energy demand and generation. However, given the peculiarity of electricity, this approach lacks control and is not yet real-life product ready. For instance, there is no assurance that a buyer will receive the full quantity of energy they have purchased since there is no known medium for transaction management. These challenges brought about an hybrid ETS structure where a platform could be developed to match the trading peers, but transaction, negotiation and agreement is solely based on the trading peers in a P2P fashion without interference of the platform as would be further discussed in Section 2.5.

2.3.2 Operation Mechanism for P2P-ETS

The next required framework for energy trading concept is the operation mechanism. Operation mechanism for P2P-ETS deals with the market and energy balancing which is related to the energy trading structure discussed in the previous section. Real-time issues such as energy balancing are not covered in most P2P-ETS market operation mechanism. In today's market, energy transactions and real-time operations are handled separately by the grid operator, where the energy trading period and lead time are defined depending on the situation. For instance, the operation mechanism in the pilot study presented in [31] is a long-term-based operation in which buyers select a provider from a list of possible providers, and the settlement is performed monthly. On the other hand, hourly-based (or shorter period) matching and transactions with short lead times are preferred in other cases, for example, in Piclo [33]. Energy transactions could be initiated by either buyers, suppliers or grid operator and could occur by using various matching methods. Therefore, the operation mechanisms for P2P-ETS are classified into four groups as follows:

- buyer select preferred provider's product: In this mechanism, a buyer select specific provider's products from a list of energy products posted by suppliers. The suppliers provide the types of generation and the selling price to the selling list, and the buyers pick from available and preferable providers [31]. This case relates to when energy is generated from different sources like renewable, solar, wind, green, etc. and consumers are able to select based on their preferences;
- grid-centered trading: In grid-centered trading mechanism, suppliers and buyers make contracts with the grid operator. The operator forms a big energy pool to trade with utilities or the power market. In this model, participating prosumers do not know how the resources are operated since they are directly controlled by the grid [32]. Therefore, in a strict sense, it is not a P2P-ETS, instead, it is more similar to a FPP system, though it is an existing solution for prosumers in the current energy market;
- buyer prioritisation and grid-matching: In the buyers' prioritisation and grid-matching mechanism, a buyer provides the preference of the energy type and/or providers instead of selecting specific providers; then, the grid matches providers and products to buyers considering buyers' preferences and real generation amounts. In this way, buyers can increase use choice even though they may not know the exact matching mechanism used [33];
- double auction-based energy trading: Double auction-based P2P-ETS models without the intervention of grid operator are proposed in research or pilot projects [92][100][101]. However, due to their operational complexity, it will be some time before this model reaches

the market. Furthermore, the basic mechanism of ideal P2P-ETS models would be similar to a conventional power market mechanism except for the existence of a larger external market that is usually an existing power market.

The last stage of the energy trading transaction is a significant role carried out by the grid operator, that of transaction settlement. Once production and consumption occur, after the transactions match, then the settlement should be performed by the grid considering the participants' performances. Mostly the settlement is made up of money in the real-world system [31]–[33], but credits or virtual money are used for trial projects [92].

2.3.3 Optimisation Techniques for P2P-ETS

The third required framework is the optimisation techniques for P2P-ETS. In energy trading, the main goal is to optimise cost either through reduction in generation cost, transport cost, energy demand or profit maximisation as discussed under the motivational factors (Section 2.1). Targets of optimisation could also be for reliability and availability of energy, the minimisation of losses, economic aspects, risk and stability criteria or various ecological interests. Optimisation problems consist of selecting the best possible solution subject to some constraints from sets of available alternatives. It involves maximising or minimising some objective function by selecting some input value from a set of allowed function values [105]. The choice of optimisation technique to apply at a particular time depends on the objective function. For instance, to minimise energy cost [56], energy losses and transportation cost [4], convex optimisation [50][51], stochastic optimisation [106][107], particle swarm optimisation [52], and linear programming (LP) [53] have been adopted.

One of the implementation methods for optimisation is game theory that provides a conceptual framework with a set of mathematical tools to analyse optimisation problems with several objective functions [108]. Within this area, game theory has been mostly applied in cost optimisation in DER [69][109][110]. There are two basic types of game theory: cooperative and non-cooperative games [111]. Players in non-cooperative game theory make decisions independently by using several frameworks to optimise and devise pricing strategies that adapt to the nature of their requirements, while players in cooperative game collaborate to achieve a common goal.

Some form of incentive is provided to aid participation in the game, which could also involve iterative and distributed algorithms to optimise the energy production and storage capabilities of users in order to reduce their monetary expenses. A known problem of DER is their intermittent supply of energy [91][100]. However, with cooperation among DER and ESSs owners, the problem could be alleviated. While this will further reduce the need for large ESSs and provide cost savings for the prosumers participating in the cooperation/coalition, it will also optimise demand and supply of prosumers within a community [91] and reduce customer loads dependence on the main grid [70]. These optimisation techniques are further discussed in Chapters 4 and 5.

2.4 Grid Constraints and Network Visibility

The preceding sections discussed the motivations, enabling technologies and the required frameworks for P2P-ETS. It is worth noting that grid constraints and network visibility is an important factor to consider in P2P-ETS systems. There are several identifiable constraints that affect the electrical grid network, its design and management are described throughout this section.

2.4.1 Grid Constraints

In bilateral trades, apart from the freedom of the prosumers to set price, P2P-ETS also allows them to make decisions to fulfil non-economic goals such as the use of energy as social capital in which the transactions are characterised by trust, goodwill and cooperation instead of pure economic motives. As the sector continues to reform, different market designs are evolving to accommodate energy trading services, especially among players at the grid edge. A key design consideration is the ability of the transacting agents or actors to respond to economic incentive or feedback signals in such a way that aligns with the operational situation of the local distribution network and the grid generally [112]. In particular, as distribution system constraints are reached or exceeded, prices associated with non-trusted transactions increase (exponentially in some cases) [112]. Alternatively, the system or market operator may issue reference prices based on the hard limits of the distribution constraints. Similar methods have previously been deployed in some wholesale markets, whereby the operators deployed locational marginal prices (LMPs) instead of dispatch instructions. In such cases, the asset owners were allowed to determine their generation output or usage in response to the LMPs [112]. This approach usurps the power of the local market operators, which may not be adequate to address the local system constraints. The mechanisms for accommodating distribution-level transactions in the face of system realities may be based on operational and technical constraints of the distribution grid, priorities established by the DSO based on operating guidelines, implicit economic values expressed in bids and offers from transactive parties or a combination of these. These same mechanisms could be used to offer new options for customers to lower energy costs, increase the use of renewable energy and better monitor and control electricity usage [113]. These are possible within the energy trading framework.

2.4.2 Network Visibility

The DSO needs clear visibility of assets and their operation within the grid to help address issues such as congestion. The prosumers, on the other hand, require guarantees that distribution capacity is always available as they trade with one another or offer energy in support of grid reliability. In such cases, the DSO needs to know the electrical and geographical location of all DER and DR assets in its domain [112]. With such visibility, the DSO may rely on the grid-edge capabilities to address local flow constraints and voltage violations [112]. To achieve this, new tools are required. Traditional analytic tools such as state estimation and power flow require detailed electrical modelling of the grid using the network topology information. Since most of the DER and DR devices are on the customer side of the meter, sometimes connected through secondary transformers, the traditional method must give way to data-driven modelling techniques. However, apart from the electrical characteristics of the network, other crucial information such as DR program, contractual constraints and prosumer preferences may not be readily available. Therefore, a structured platform is required to harness these pieces of data from various sources and provide consolidated information to the DSO from which the system state can be evaluated. This implies that all energy trading actors and assets must be capable of exchanging information with the energy trading platform.

2.5 Prospects of P2P-ETS

From the preceding sections, the prospects of P2P-ETS management are becoming somewhat obvious. The recommendations made are based on the potentials, merits and demerits of the subtending techniques, algorithms and technologies contributing to a dynamic and sustainable energy transaction management system and are given in this section, which also serve as the basis for the P2P-ETS platform developed in Chapter 6.

As seen in the previous sections, coordination and transaction management are required by the actors. Prosumers therefore require a platform where they can actively engage to share or trade energy. The P2P-ETS platform should support real-time transaction and information exchange among prosumers, be scalable, i.e. accommodate an increasing number of prosumers, and have capacity to manage prosumers' energy profiles. In the succeeding paragraphs, some recommendations towards a P2P-ETS platform are provided, they integrate both distributed and centralised control features.

On the P2P-ETS platform, prosumers can list their energy profile including, energy generation capacity, location, tradeable quantity and offer price. The location of energy generation is paramount as this will help in facilitating neighbourhood energy trading and minimise the environmental impact caused by energy loss due to long transmission distances. Energy offer price can be determined by each actor by solving a local optimisation problem [4] to determine the equilibrium price to trade/buy energy as a function of the total cost of production/transportation including energy losses. For instance, each actor pursuing selfish or altruistic goals can model the optimum energy price as a non-cooperative game with each actor defining its objective function and different pricing strategies to optimise profit.

Subsequently, each actor will register its details including some basic information on the platform after determining the energy offer price. The information is stored on the platform database, and non-sensitive information is published on the platform (including trading profile, trading position relative to others and energy location). On registering, a prosumer who desires to buy energy will make an enquiry to the energy listings database, enabling them to decide from whom they want to buy using their own preference metrics. The metrics are not limited to distance, cost and reliability. A potential seller can be matched to a potential buyer using matching or an auction game[12]. When a suitable provider is found, the buyer queries the platform for the provider details to establish direct communication. This implies that each actor is able to query the platform to locate/discover a suitable provider, but communication and negotiation is carried out directly between actors in a P2P fashion. To establish communication between the seller and the buyer, a cooperative game, e.g., a coalition game can be modelled, which will be subject to some defined objective function.

Once a potential buyer has been matched to a potential supplier, the platform will handle the transaction management process. For instance, after a buyer communicates with a possible provider and both parties negotiate and agree to the terms and conditions of trade, direct trading is established. The platform applies an optimisation model [101] to manage a dispute if one arises among the prosumers. The P2P-ETS platform will also ensure that the energy gets to the buyer whilst the credit gets to the seller. The optimisation technique applied on the platform will determine the optimal power transmission path to reduce transmission loss [114]. The process is presented in Figure 2.5, and summarised as:

- Non-cooperative game models modelled for each actor to determine its energy offer and bid price. Each actor optimises its individual objective functions using different game theory tactics and different pricing strategies to optimise profit. The objective of each player is to determine the optimal quantity and price at which it wants to trade energy to maximise profit.
- The platform implements auction theory (double auction) and matching game from game theory to match a potential buyer to a seller based on some predetermined constraints.
- Communication amongst buyers and sellers would be implemented by using a distributed algorithm based on graph theory subject to some defined objective functions and some constraints, e.g., transmission link capacity and actor data processing capacity.
- The platform determines the optimal path for the energy transmission using a distributed algorithm and will also determine how the seller

[12]matching based on different preferences like price, quantity of demand/supply, location, etc.

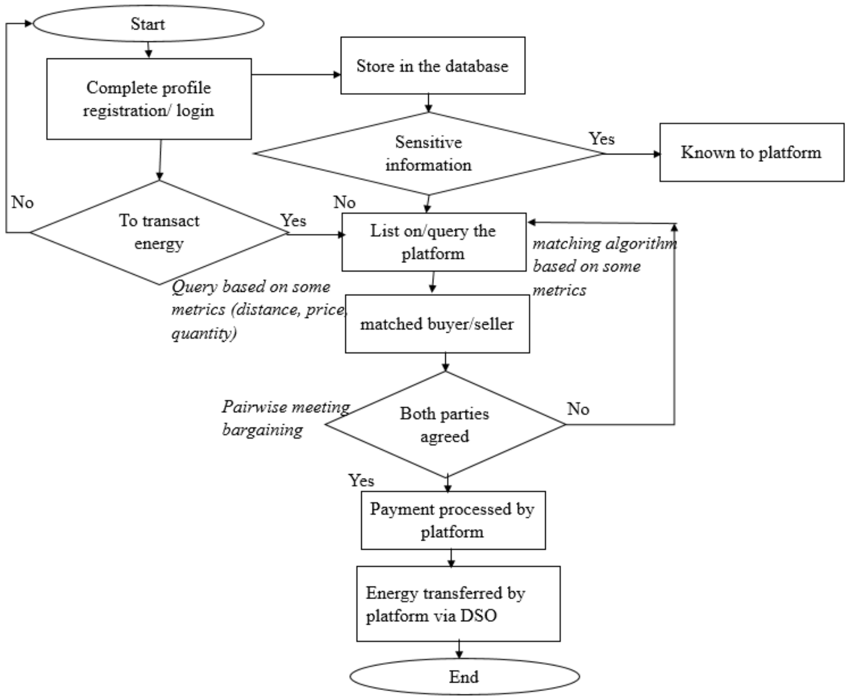

FIGURE 2.5: A proposed P2P-ETS platform algorithm for distributed energy transaction and management.

will be reimbursed.

2.6 A Four-layered P2P-ETS Architectural Model

The European Standardisation Organisation proposed the Smart Grid Architecture Model (SGAM) [115] for continuous standard development of smart grid. The architecture is as shown in Fig. 2.6 with five layers. The layers include the component, communication, information, function and business layers. While the SGAM architecture mainly focused on smart grid, study [89] adopted the architecture to propose a four layer architectural model for P2P energy trading. The four layers proposed include the power grid, ICT, Control and business layers.

Based on the SGAM and SONA, a P2P-ETS architecture is proposed shown in Fig. 2.7, in order to summarise and categorise how the key concepts and technologies of P2P-ETS interrelate. SONA is used to illustrate that each component has its own task or service and the various components communicate with other components within the network using a communication protocol. All the components synergise to support the target application, in this case, energy trading.

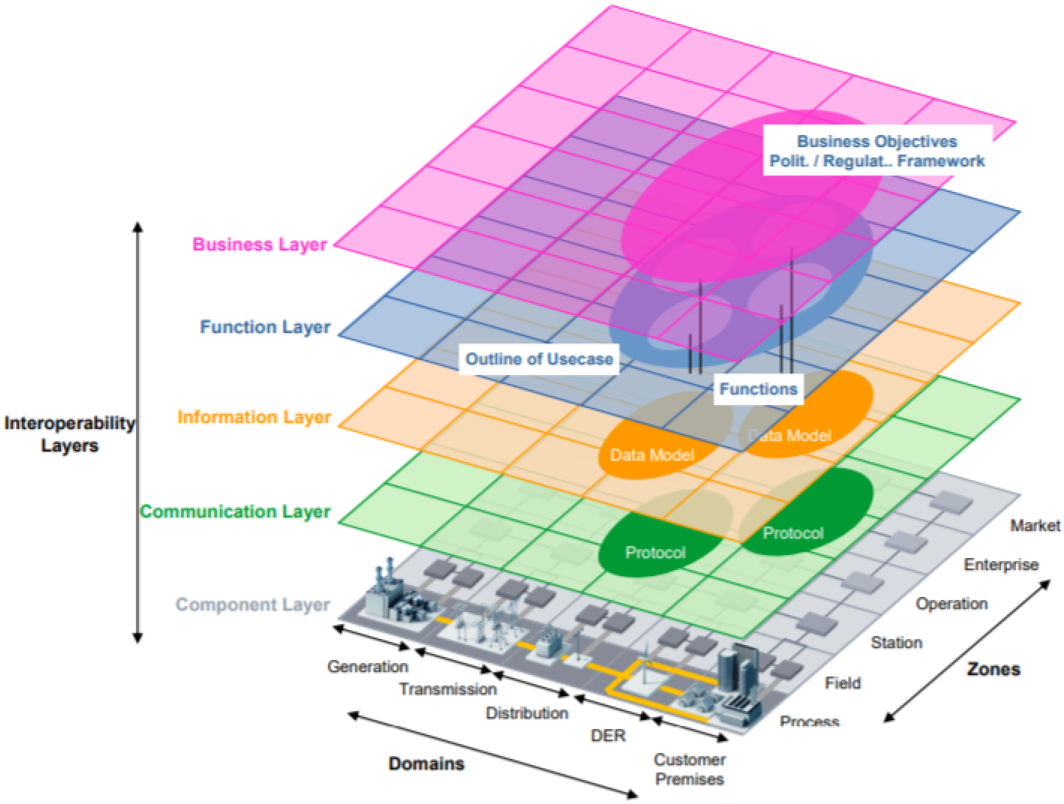

FIGURE 2.6: Smart Grid Architectural Model [115].

The architecture illustrated in Fig. 2.7 comprises of four-core-layers; physical, system protection, control, and platform & market operations. Differ from the SGAM architecture, communication, security, governance and business models are cross-layer components because they are applicable to all the layers. The layers are introduced as follows.

The physical equipment layer consists of all the physical components already discussed under the enabling technologies in Sections 2.2.1 and 2.2.2. These components form the physical power grid network to foster P2P-ETS.

The systems protection and control layer consists of models and protocols to protect the physical layer equipment from unauthorised access[13]. This is paramount so as not to hinder the target application; energy trading.

The control layer is a core layer consisting several distributed monitoring, scheduling, optimisation and dispatch algorithms to enable the functionality of the P2P-ETS. It basically involves control strategies for preserving the quality and reliability of power supply, as well as optimising

[13] Although security and system protection is paramount for the target application, it is not discussed in this thesis. This feature is considered as a possible future outlook of P2P-ETS

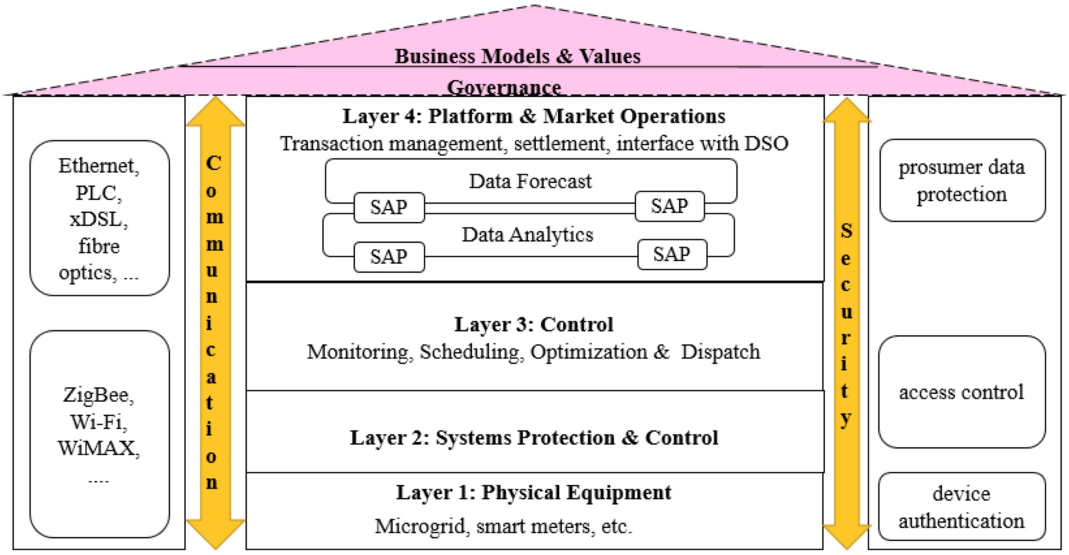

FIGURE 2.7: A Four-layered P2P-ETS architecture model

the utilities of the traders. Chapters 3, 4, and 5 of this thesis discuss this layer in detail.

Layer 4 comprises of the platform and market operation layer. This layer defines the platform operation as well as the market mechanism incorporated for P2P-ETS. The implementation of this layer is discussed in Chapter 6

Communication is a cross-layer component of the architecture already discussed in Section 2.2.3 under enabling technologies (ICT). Security is also a cross-layer component of the architecture. Governance refers to different government policies acting as enablers or barriers to P2P-ETS. While business and value determine how energy is traded among the connected peers on the platform. The business and value can implement several trading scenarios to accommodate different players in the market. For instance, trading based on flexibility of demand/supply, time of use, capacity of each players, resources owned e.g. battery storage, etc.

2.7 Challenges and Gaps

The ambition to harness DER and trade energy between prosumers is uncovering new possibilities. In actualising energy trading between prosumers, one of the key considerations is how to manage the interactions among the DSO, prosumers and other system operators and actors on the P2P-ETS platform. Generally, it is established that coordination between the actors is necessary; however, stakeholders differ on modality. While most assume perfect communication among energy trading peers [7], [116], some neglect the pricing mechanism during energy trading [3], [47]. In addition, the platform for P2P energy trading has not been standardised. Robust and lightweight distributed algorithms that can efficiently route messages between the prosumers and dynamically managed the network have not been discussed. Lastly, an optimal path for energy transmission among the prosumers using distributed algorithm has not been fully investigated [117]. These identified challenges and gaps form the basis of this thesis, for developing several distributed algorithms for optimised path, data routing and energy dispatch, with the ultimate aim of developing a P2P-ETS platform which will incorporate these algorithms.

2.8 Methodology

The central argument in this thesis is that, incorporation of P2P-ETS into the existing energy grid provides some unique opportunities to improve energy efficiency. However, this can only be actualised with some enabling technologies and frameworks. Characteristics and limitations along with variations of technologies have been discussed to identify the potential gaps in fully optimising the potentials of P2P-ETS. This thesis investigates distributed algorithms that can facilitate optimised energy transfer path, matching based on actor preferences, data routing, energy dispatch and utility maximisation of energy traders. In view of this, Chapter 3 develops distributed algorithms for an optimised path between producer and consumer, as well as matching algorithm influenced by distance metrics. Chapter 4 investigates data coordination algorithms among the distributed actors. Chapter 5 introduces distributed algorithm for energy dispatch and utility maximisation. The distributed algorithms for optimised path, data routing, and energy dispatch among peers will be investigated and simulated using Java programming language as well as in MATLAB. These algorithms inform the design of market based P2P-ETS platform reported in Chapter 6 achieved using Python programming language.

2.9 Chapter Summary

This chapter discussed the energy trading concept, technologies, frameworks, network constraints, visibility and prospect of P2P-ETS. It began with the introduction of the concepts, it's motivation, enabling technologies and microgrid applications including its communication requirements and required frameworks. Furthermore, this chapter discusses the prospect of P2P-ETS, with a recommendation of an ideal P2P-ETS platform that would be used in developing the platform in Chapter 6. In addition, the existing literature on ETS frameworks was reviewed and classified based on structures, controls, trading methods, optimisation techniques and communication models. Important issues such as grid constraints and visibility are also covered. On the prospects of P2P-ETS, it was identified that employing a hybrid energy trading structure is vital to the realisation of P2P-ETS. Going further, Chapter 3 discusses path optimisation and prosumers' matching on the P2P-ETS platform.

Chapter 3

Path Optimisation and Prosumers Matching

IN P2P-ETS, the first communication goal is to ensure all messages transmitted are received by the appropriate party within acceptable delay margins. This is because real-time or near real-time transactions are involved, and a significant delay in routing the energy request information among the peers in the network could result in failed transactions. In practical system design, locality is a requirement prior to offering the application services, such as resource finding, resource sharing, data aggregation, data routing, etc. As discussed in Chapter 2, that energy transmission loss and other associated costs are largely dependant on the distance it travels. Thus, another important goal in P2P-ETS is to provide each prosumer an efficient method to reach their energy trading target utilising an optimised path based on distance metrics applications.

Path optimisation is a fundamental network problem. The aim is to minimise the weights of the edges connecting two nodes in the network, offering practical applications in cyber-physical systems ranging from wireless sensor networks [118], supply chain networks [119] and smart grid [120] etc. Several techniques have been proposed for shortest path problems including the Dijkstra algorithm for single source problem originally proposed by Edsger [121], Bellman-Ford algorithm for finding the shortest path from a single source to every other nodes in the network [122], etc. Although these algorithms solve the initial shortest path problem, their computation time is excessive when the network scale becomes large [123]. To address the computational complexity, nature-based algorithms including bioinspired algorithms like genetic algorithm, particle swarm optimisation and ant colony optimisation have emerged [123]. Recently, the capability of *Physarum Polycephalum* also known as slime mould dynamics has been shown to offer efficient algorithms in solving many graph problems including network design [124], shortest path [119][123], network formulation and simulation [125], in applications ranging from wireless sensor networks, to load shedding in MG [126]. This chapter introduces a slime mould-inspired approach to smart grid for finding an optimised path between an energy producer and a consumer, that satisfies the latency requirements of MGs discussed in Chapter 2, taking efficiency, robustness and costs into account[1]. The remaining sections of this chapter are organised as follows: the challenge to prosumer's discovery is introduced in Section 3.1, the problem formulation of the slime mould based locality algorithm is presented in Section 3.1.1. Evaluation of the developed model is discussed in Section 3.2, while Section 3.2.5 discusses an application to optimal path for energy transmission. Section 3.3 discusses an extension to the algorithm for energy matching between a producer and consumer as well as its numerical example and the results. Section 3.4 summarises the chapter and draws conclusions.

3.1 Prosumer's Discovery in Energy Trading Network

Shortest path finding algorithms are used to find the minimum weighted or most efficient path in the network. They are used to identify a path or route between two vertices such that the sum of the weights of its constituent edges are minimised. This is equivalent to finding the optimal and also the alternate paths for transmitting the power from a generating station to consumer ends [127]. Take for instance, Fig. 3.1 which illustrates the power and communication connection between different actors including prosumer, consumer and the grid. To transmit power from the grid to the consumer, the optimal path would be to transmit through the connection to the prosumer, then to the consumer. Same analogy applies to other actors illustrated in Fig. 3.1.

[1]The costs in terms of reducing the connecting links between prosumers, by eliminating those links that are not optimal route. While this chapter is motivated for optimal route among prosumers, it can be extended to realise optimal path for energy transmission in power distribution network, further discussed in Section 3.2.5.

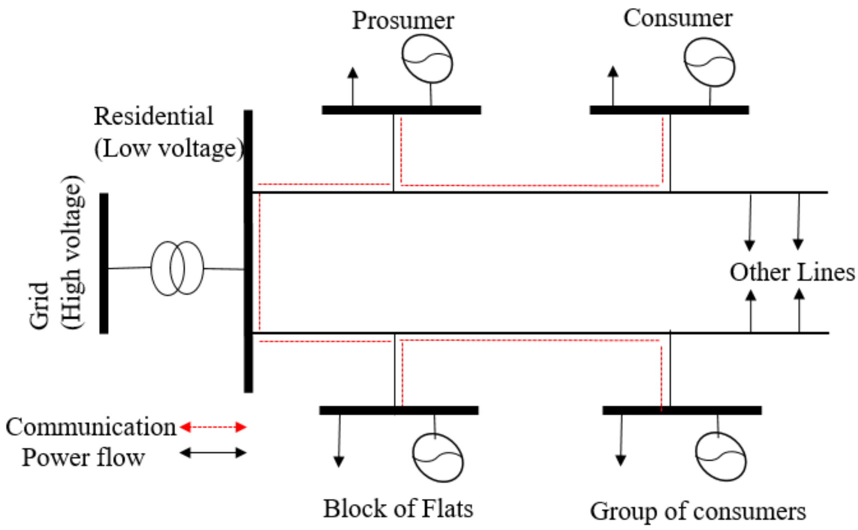

FIGURE 3.1: Benchmark of MG connection to the grid (adapted from [128]

By integrating the complex network[2] and evolutionary algorithm concepts, a multi-objective minimisation function that combines cost elements, related to the number of electric cables (graph links), and several metrics that quantify properties beneficial for smart grid including energy exchange at the local scale (considering high robustness and resilience) can be modelled [129]. A method to manage the active power in the distribution systems using an application of the graph theory, specifically, the successive shortest path algorithm, is introduced in study [130], for optimal power generation, dispatch and power flows. The algorithm is implemented in a distributed manner with simulations to model its efficiency in cases of optimal operation, congestion management, and power generation cost. Furthermore, in minimising time-out delays in the power system network during outages, the authors in [127] suggests transmitting power through the optimal path for quick reconfiguration of power system components using the Bellman-Ford algorithm. The solution is modelled for a given set of generation, load pair, optimal path considering the capacity of the transmission line, voltage stability, shortest path achieving minimum losses, priority of loads, and power balance between the generation and demand. This restorative path search guidance tool is quite efficient in finding the optimal and also the alternate paths for transmitting the power from a generating station to the point of demand.

From the foregoing, Dijkstra, Bellman-Ford and Kruskal's algorithms are

[2]In its most basic definition, a complex network is a graph modelling of real-world networks such as social networks, transportation, power grid, etc..

examples of single objective shortest path algorithms used in the smart grid applications discussed. These algorithms track shortest paths from a single source to one determined node in the graph and find shortest paths independently [120]. However, according to the structure of power networks, it is sometimes necessary to find shortest paths from one centered bus and/or multiple points to multiple units (e.g, phasor measurements units) buses simultaneously checking overlapped paths in the routing problem. This requires a multi-objective shortest path algorithm to find the best solution routes for connecting smart grid components to guarantee the information transmission flow [120]. In the same way, for P2P-ETS where prosumers are distributed and diverse, a shortest path finding algorithm with distance constraints to establish an optimised path among connected peers in parallel is of most importance. Parallel execution reduces the network computation time and improves efficiency. This would not only result in low cost, but would also reduce the search time significantly[3] especially in large network as P2P-ETS. Utilising the proposed *Physarum Polycephalum*, the parallel execution of shortest path among distributed connected peers can be achieved. Thus, this current chapter develops a slime mould inspired path optimisation and matching algorithm to first determine the optimal path between a consumer and a producer, secondly, to route energy demand between them, which is then extended to match or pair a consumer to the closest distance-based producer. [4].

3.1.1 Problem Formulation: Communication Network

In this section, we introduce the network modeling used in the thesis, particularly in Chapters 3, 4 and 5. Consider an energy network model that focuses on the communication process[5] amongst actors[6] with the objective to ensure seamless information exchange. Thus, each actor $(i = 1, \cdots, N)$

[3]This is an important feature especially in a large network. Parallel execution reduces the network computation and improves efficiency. Impact of this parallel execution would be discussed in Section 3.2.6.

[4]As discussed in Chapter 2, distance charge is a significant amount to electricity bill paid in the UK, as well as related $C0_2$ emission, thus distance metrics is a desirable property on the P2P-ETS platform.

[5]This chapter models the message routing and locality algorithm among prosumers at the tertiary level of control without explicitly touching the physicality of the underlying distribution network such as power flow analysis.

[6]As defined in Chapter 2, actors are the entities interacting on the P2P-ETS platform consisting of consumer, producer, prosumers, DSO, etc. Where appropriate, the particular actor would be specified.

has its computed energy needs to be communicated in the network. For instance, actor i is a producer that desires to sell energy to consumer j, thus sending a transactional message to consumer j. Producer i is identified as the source of information exchange, and Consumer j as the sink, a recipient of the information. The energy network is described as a connected graph

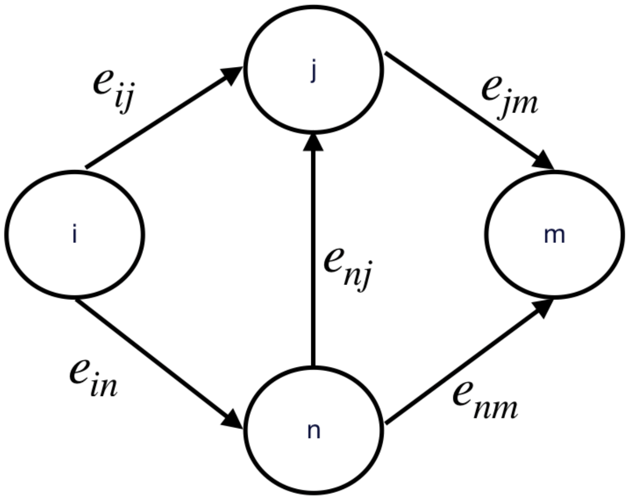

FIGURE 3.2: A multi-commodity flow network showing connectivity among 4 vertices

$G = (V, E)$, where $V = \{1, \cdots, N\}$ denotes the set of actors as shown in Fig. 3.2 (a nodal representation of Fig. 3.1). G is a strongly connected directed graph, where every node in the network is reachable from every other node, i.e., there exists a directed link $e_{ij} \in E$ denoted by (i,j) from node n_i to node n_j in the network as shown in Fig. 3.2. $E(t) \subseteq V \times V$ is a set of links that changes over time according to the state of the link at time, t. Each directed link is characterised by its capacity, $c_{i,j}$, and the traffic flow, $x_{i,j}$. For each link, $\mathbf{A}$ denotes the set of the link weights which denotes the link costs. Representing $|V|$ as n, then $\mathbf{A}$ can be expressed as the symmetrical adjacency matrix of (3.1). Where $A_{i,j}$ denotes the weight along link (i, j) and expressed as:

$$\mathbf{A} = \begin{bmatrix} 0 & A_{12} & A_{13} & \dots & A_{1n} \\ A_{21} & 0 & A_{23} & \dots & A_{2n} \\ A_{31} & A_{32} & 0 & \dots & A_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_{n1} & A_{n2} & A_{n3} & \dots & 0 \end{bmatrix} \tag{3.1}$$

Given a source node $i \in V$, a sink node $j \in V$. Function $\bar{\Phi}_{i,j}(x_{i,j})$ represents the cost of path P traversed to send a message flow $x_{i,j}$ from i to j. The optimised cost path problem can be formulated as

$$\min \sum_{P \in P(i,j)} \bar{\Phi}_{i,j}(x_{i,j}) \tag{3.2a}$$

$$s.t: x_{i,j} \leq c_{i,j}, \qquad \forall i,j \in E, \quad p \in P \tag{3.2b}$$

$$x_{i,j} \geq 0, \qquad \forall i,j \in E, \quad p \in P \tag{3.2c}$$

where $P(i,j)$ represents the set of all paths from producer n_i to consumer n_j. Equation (3.2b) is the capacity constraints that suggests that the traffic flow $x_{i,j}$ to be less than the capacity of the link $c_{i,j}$, while (3.2c) is the non-negativity constraints meaning that, there should be a positive flow from n_i to n_j.

3.1.2 Physarum Polycephalum Algorithm

Physarum polycephalum forms a dynamic tubular network connecting peers. The diameters of the tubes carrying large fluxes of flows grow to expand their capacities and tubes that are not used decline and disappear entirely. The segments of tubes of slime mould are edges of a graph network, with intersection point representing the nodes. The parameter $Q_{i,j}$ represent the flux on the tubes connecting node n_i to node n_j. According to Kirchoff's law and law of conservation, the flux of input at a source is equal to the total flux of output at all node sets [131], [132]. Also, at any other nodes, the sum of flux flowing in is equal to the sum of flux flowing out [132]. These exposition follows studies [131], [132]. The flow conservation is expressed as:

$$\sum_j Q_{i,j} = \begin{cases} -I_o, & \text{for j = source} \quad (3.3a) \\ I_o, & \text{for j = sink} \quad (3.3b) \\ 0, & \text{otherwise.} \quad (3.3c) \end{cases}$$

where I_o is constant and represents the flux flowing from the source node or into the sink node. Assuming the flow along the tubes is approximated by Poiseuille flow[7], the flux $Q_{i,j}$ can be calculated as expressed in (3.4),

$$Q_{i,j} = \frac{D_{i,j}}{L_{i,j}}(p_i - p_j) \tag{3.4}$$

[7]Poiseuille's flow is the steady flow in an infinitely long, circular pipe caused by a pressure gradient. It is expressed as $Q = \frac{\pi r^4 P}{8\rho L}$ where ρ is the constant fluid viscosity (which is often ignored in the slime-mould equation), L is the length of the pipe, r is the radius of the pipe and P is the pressure difference between the ends

where $D_{i,j}$ is the conductivity of the tube, $L_{i,j}$ is the length of the link and p_i is the pressure at node i. To calculate the pressure on each node, equation (3.4) is substituted in (3.5) as:

$$Q_{i,j} = \frac{D_{i,j}}{L_{i,j}}(p_i - p_j) = \begin{cases} -I_o, & \text{for j = source} \quad (3.5a) \\ I_o, & \text{for j = sink} \quad (3.5b) \\ 0, & \text{otherwise.} \quad (3.5c) \end{cases}$$

By setting p_j to the basic pressure level of $p_j = 0$, all p_i and $Q_{i,j}$ can be determined. To model the adaptive behaviour of the slime mould, the conductivity $D_{i,j}$ is believed to change overtime as the flux increases or decreases, resulting to evolution of $D_{i,j}$ as

$$\frac{\delta D_{i,j}}{\delta t} = f(|Q_{i,j}|) - \gamma D_{i,j} \tag{3.6}$$

where γ is a constant that represent the decay rate of the tube[8]. Equation (3.6) is called the adaptation equation, as the conductivity diminishes when the flux on the links is zero and increases by the amount of flux on the link. f is assumed to be monotonically increasing continuous function satisfying $f(0) = 0$. Assume $f(|Q|) = |Q|, \gamma = 1$, Physarum can always converge to the shortest path [132]. For an iterative process, and adopting the functional form $f(Q) = |Q|$, (3.7) is used instead of (3.6) to calculate the conductivity of the link as

$$\frac{D_{i,j}^{t+1} - D_{i,j}^{t}}{\delta t} = \alpha |Q_{i,j}^{t}| - \gamma D_{i,j}^{t+1} \tag{3.7}$$

$D_{i,j}^{t}$ is the value of $D_{i,j}$ at the t^{th} iteration time.

Thus, based on the feedback from the iteration, a critical link would be preserved and others would be deleted, thus forming a Physarum spanning tree. Other algorithms solve problems by progressing step-by-step in a single direction, the slime mould algorithm works by sampling a variety of directions in parallel. Based on the samples, it discards less optimal directions to progress toward the solution. After adaptation, the algorithm selects another set of sources and sink nodes and repeats the calculations. **Example 1.** Consider the network shown in Fig. 3.3, the shortest path between node 1 and 5 needs to be determined. The number along the edge represents the weight of the edge. Each source node creates unit flow of

[8] γ ensures the convergence of the algorithm when the value is set to 1.

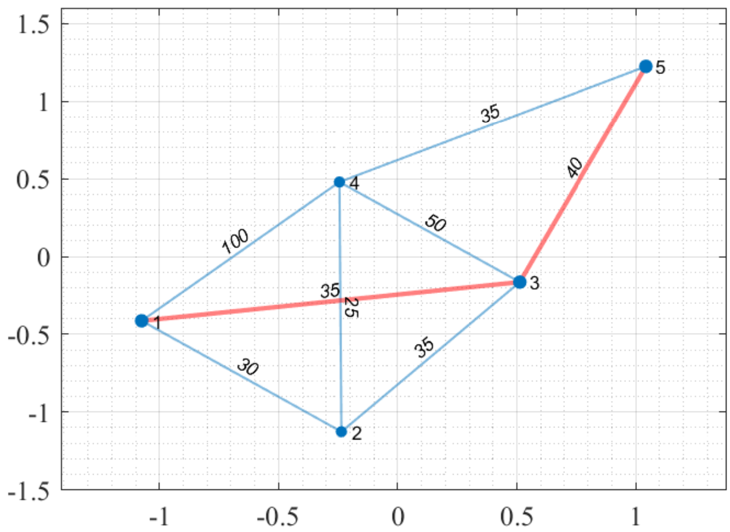

FIGURE 3.3: Bidirectional communication network Showing the Least Cost Path from Prosumer 1 to Prosumer 5.

demands and the demands are consumed at destination nodes called sinks To start the implementation, the conductivity is first initialised, as the flux moves along the edges, the conductivity is recorded as shown in Fig. 3.4. It can be observed that the flux along edges $(1,3)$ and $(3,5)$ converged to 1 signifying the shortest path, with same result evidence from other traditional algorithms including Dijkstra algorithm, but with a longer convergence time. Here, convergence is achieved when the strongest flow moves from the source to the sink using the least cost shortest path and remained constant (the flux of each arc do not change any more) until the end of the simulation. In Section 3.2.6 there will be further comparison

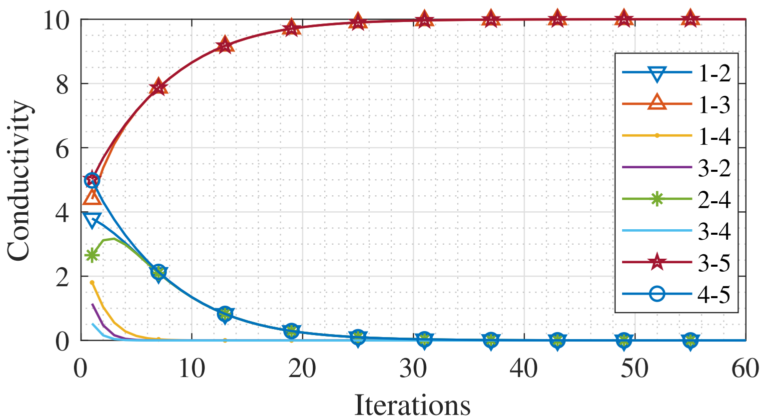

FIGURE 3.4: The changing trend of the conductivity on each edge.

result of the convergence time with the traditional algorithms. Interestingly, if there is a unique shortest path from source to sink and the dynamics stabilize, the diameter of edges on the shortest path converge to > 0, or 0 otherwise, which means, the link constraint enforce unused links to zero thereby removing such links from the design. This suggests that other paths except the optimised one can be successfully removed/deleted from the network design, thus saving cost in terms of eliminating redundant links in the network.

3.1.3 An Application to Optimised Path Among Prosumers

In distributed optimisation where prosumers are interacting through message exchanging, their interaction is dependent on the minimum cost path in the networks as well as the capacity of the communicating links. Each peer aims to interact using an optimised path with least cost communication links to every other peer in the network. The peers iterate to improve their costs until equilibrium is achieved, meaning no interacting prosumer can further reduce its cost by switching to alternate route. Slime mould can model both the shortest path cost and the capacity constraint of the connecting/transmission link. This combination is one of the greatest strength of this scheme compared to other algorithms that only models shortest path problems.

The physarum algorithm is modified for energy network optimisation as follows. Nodes are defined as energy producers, consumers and prosumers, links are communication links connecting the consumers to the producers. In a P2P-ETS, energy producers could assume role of consumers or prosumers. A single source, single sink of the original Physarum model of 3.5 is extended to provide multiple sources, multiple sinks for distributed implementation expressed in (3.8)

$$\frac{D_{i,j}}{A_{i,j}}(p_i - p_j) = \begin{cases} -\sum\limits_{j \in N} I_o^{i,j}, & \text{for j = source} \quad (3.8a) \\ \sum\limits_{j \in N} I_o^{i,j}, & \text{for j = sink} \quad (3.8b) \\ 0, & \text{otherwise.} \quad (3.8c) \end{cases}$$

where $I_o^{i,j}$ represent the message flow between producer i and consumer j, $A_{i,j}$ is the distance cost on the link. In the physarum model, the flow on each link is continuous during iterations, the costs on each link is updated with the flow based on peer activities at time t. Those algorithms only reflect the link length attributes (to calculate the shortest distance), whereas, message routing has two attributes: message flow (equivalent to the energy demand message) and the link cost (the edge weight as a function of the flow). The developed algorithm is presented in **Algorithm 1**. The presented algorithm could also be said to calculating the shortest path to a closest clusterhead (represented as sinks) in cases of clustering of peers for particular application, i.e, to reduce communication delay as presented in study [131]

Algorithm 1: Proposed Optimised Path Algorithm for Prosumers

1: ***Input:*** *The graph* $G = (V, E)$, *the distance cost* $A_{i,j}$, *total flow traffic* $D_{i,j}$, *the demand flow* $Q_{i,j}$, γ, *and the step-size,* α, *for all* $i \in N$

2: $p_j = 0$,

3: $t > 0$,

4: ***Calculate*** p_i, *according to (3.8)*

5: ***Update*** *the demand flow* $Q_{i,j} = \dfrac{D_{i,j}}{A_{i,j}}(p_i - p_j)$

6: ***Update*** $D_{i,j}$ *(3.7),* $\forall j \in N$

7: *Go to next time slot until maximum time-step is reached*

3.2 Numerical Simulation and Result Analysis

To test the effectiveness of the proposed optimised path solution, a test network case consisting of 10 prosumers[9] is first carried out as shown in Fig. 3.5. Simulations are performed in MatLab using random graphs which are presumed to represent real-world distributed systems. Setting α^{10}= 1 and $\gamma^{11} = 1$, these scenarios are implemented:

[9] As discussed in Chapter 2 methodology that a fairly sized microgrid number between $4 - 10$ would be utilised in this thesis.

[10] α serves as a multiplier to calculate the value of $D_{i,j}$ from the message flow $Q_{i,j}$. For instance, if the flow is 10, α is 0.1, the $D_{i,j}$ would be 1.

[11] setting γ to 1 ensures the convergence of the algorithm.

3.2.1 Single Producer and Single Consumer

The convergence of the system is achieved when the flow runs from the source to the destination on a shortest path and remains till the simulation ends. Since this is the single producer-consumer pair problem, the calculations of step 4 of **Algorithm 1** is according to (3.5). Result of the total demand convergence is illustrated in Fig. 3.6, while Fig. 3.5 shows the

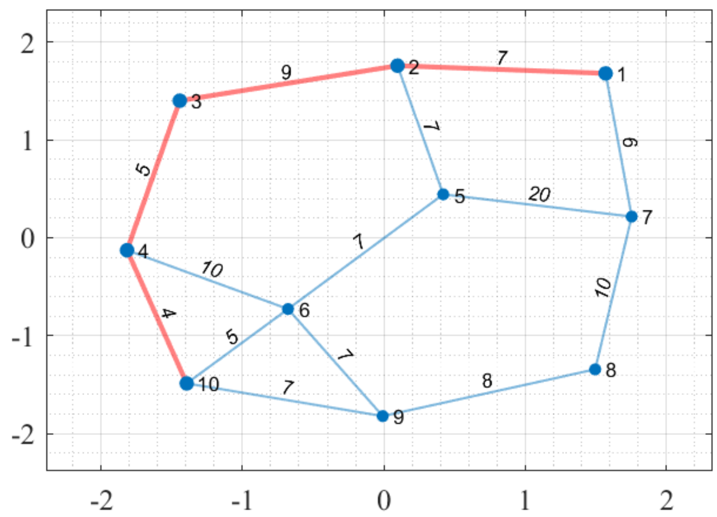

FIGURE 3.5: Bidirectional communication network showing the least cost path from producer 1 to consumer 10.

energy network with the weights on the links. This demonstrated that the proposed solution solves the network problem by first locating the consumer using the least cost path, and then transmitting a demand value of $10kWh$ from Producer 1 to Consumer 10, as evident in Fig. 3.6, the total flow on edges $1 \longrightarrow 2 \longrightarrow 3 \longrightarrow 4 \longrightarrow 10$ converged to $10kWh$ indicating the shortest path from Producer 1 to Consumer 10, while the conductivity on other edges converged to 0.

3.2.2 A Single Producer and n Consumers

For the case of connecting a single producer to multiple consumers, the calculations of step 4 of **Algorithm 1** is given as

$$\frac{D_{i,j}}{A_{i,j}}(p_i - p_j) = \begin{cases} -I_o, & \text{for j = source} \quad (3.9a) \\ \sum_{j \in N} I_o^{i,j}, & \text{for j = sink} \quad (3.9b) \\ 0, & \text{otherwise.} \quad (3.9c) \end{cases}$$

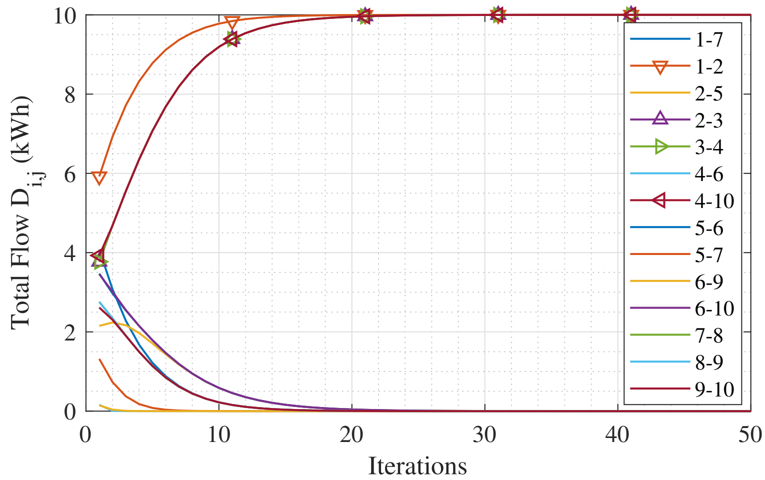

FIGURE 3.6: The demand flow on each link for single producer to single consumer.

The resulting flow plot of transmitting a demand of 10kWh from Producer

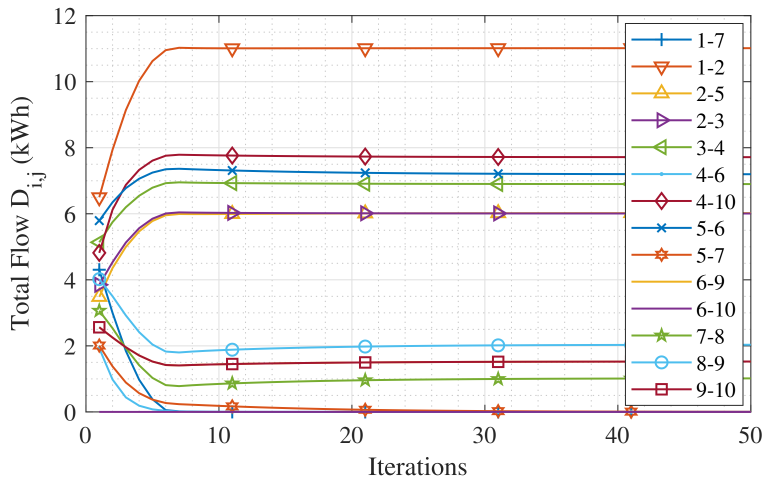

FIGURE 3.7: The demand flow on each link for single producer to multiple consumers.

1 to Consumer 6 and 10 of the network layout of Fig. 3.5 is illustrated in Fig. 3.7. The plot demonstrated the total flow on each link, with higher flows on the optimal path to the destination. For instance, the flow on links $1 \longrightarrow 2 \longrightarrow 3 \longrightarrow 4 \longrightarrow 10$ and $1 \longrightarrow 2 \longrightarrow 5 \longrightarrow 6$ are the highest. While $7 \longrightarrow 8 \longrightarrow 9 \longrightarrow 10$ shows alternate path (less optimal) to the destination consumers. In addition, the other links converged to 0, since they are not involved in the optimised path to the consumer.

3.2.3 n Producers and a Single Consumer

In this settings, the demands are set to flow from multiple producers in the network directed to a single consumer. With this configurations, the calculations of step 4 of **Algorithm 1** is according to:

$$\frac{D_{i,j}}{\mathbf{A}_{i,j}}(p_i - p_j) = \begin{cases} -\sum\limits_{j \in N} I_o^{i,j}, & \text{for } \text{j = source} \quad (3.10a) \\ I_o, & \text{for } \text{j = sink} \quad (3.10b) \\ 0, & \text{otherwise.} \quad (3.10c) \end{cases}$$

Similarly, from the total flow convergence of Fig. 3.8, it can be observed that

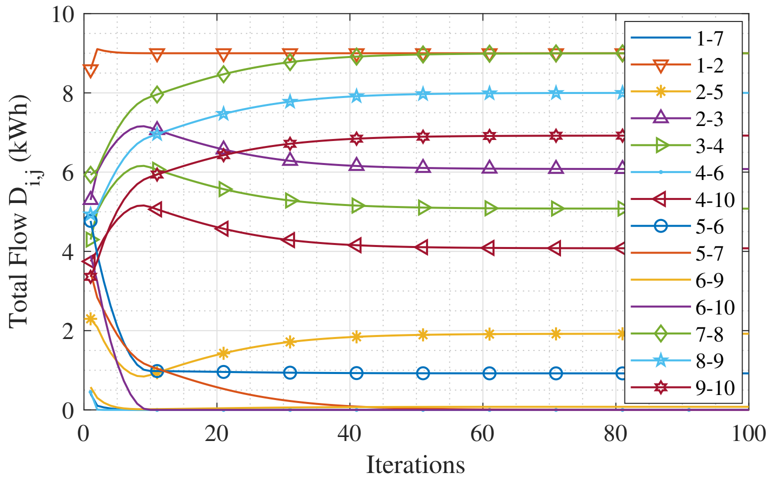

FIGURE 3.8: The demand flow on each link for multiple producers to single consumer.

the route 1 $\longrightarrow$ 2 $\longrightarrow$ 3 $\longrightarrow$ 4 $\longrightarrow$ 10 and 7 $\longrightarrow$ 8 $\longrightarrow$ 9 $\longrightarrow$ 10 converges to higher flow value than the other links 2 $\longrightarrow$ 5 $\longrightarrow$ 6. While other unused links converged to 0.

3.2.4 n Producers and n Consumers

Further, setting some prosumers as producers and some as consumers, and transmitting a demand of 10kWh among them, in this case, two consumers. Similarly, the calculations of step 4 of **Algorithm 1** is according to (3.8). The convergence result of Fig. 3.9 demonstrates that the proposed optimised path algorithm solves the network problem by transmitting demand values of 10kWh each from producers 1 and 7 to consumers 4 and 10 using the least cost path. i.e., using edges 1 $\longrightarrow$ 2 $\longrightarrow$ 3 $\longrightarrow$ 4 and 7 $\longrightarrow$ 8 $\longrightarrow$ 9 $\longrightarrow$ 10, while other links converged to 0.

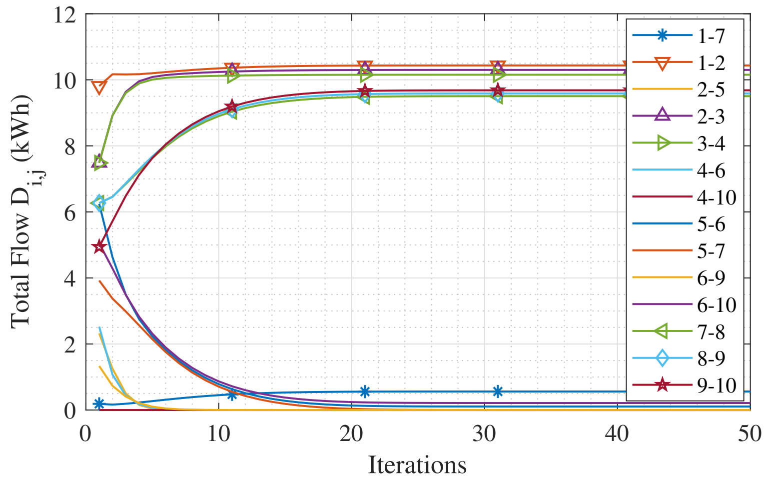

FIGURE 3.9: The demand flow on each link for multiple producer to multiple consumer.

3.2.5 Optimal Path for Energy Transmission in Distribution Network

While the previous sections are motivated by optimal path based on distance cost between producers and consumers, the solution proffer can be extended to realise optimal path for power transmission in a capacitated network. Thus, the power flow optimisation is defined as a minimum cost flow problem relating to both shortest optimised path and maximum flow capacitated problem [130]. This section's focus is on optimal path for energy transfer in a capacitated network. As defined in Section 3.1.1 that each link is characterised by two non-negative attributes $c_{i,j}$, capacity and $A_{i,j}$, distance cost. Given a source node $i \in V$, a sink node $j \in V$. Function $\bar{\Phi}_{i,j}(x_{i,j})$ represents the optimisation problem defined in (3.2a). $c_{i,j}$ is the capacity of the link i, j that ensures the transmission line is not congested, as well as to maintain a maximum flow of power for control purposes. The traditional solution to solving the maximum cost flow problem is the successive shortest path algorithm, which has been discussed to have higher computational time. Thus, using the proposed slime mould solution, the single source single destination formulation is given as

$$\frac{D_{i,j}}{A_{i,j}} c_{i,j}(p_i - p_j) = \begin{cases} -I_o, & \text{for j = source} \quad (3.11a) \\ I_o, & \text{for j = sink} \quad (3.11b) \\ 0, & \text{otherwise.} \quad (3.11c) \end{cases}$$

followed by substituting (3.11) to step 4 of **Algorithm 1** for the capacitated flow optimisation.

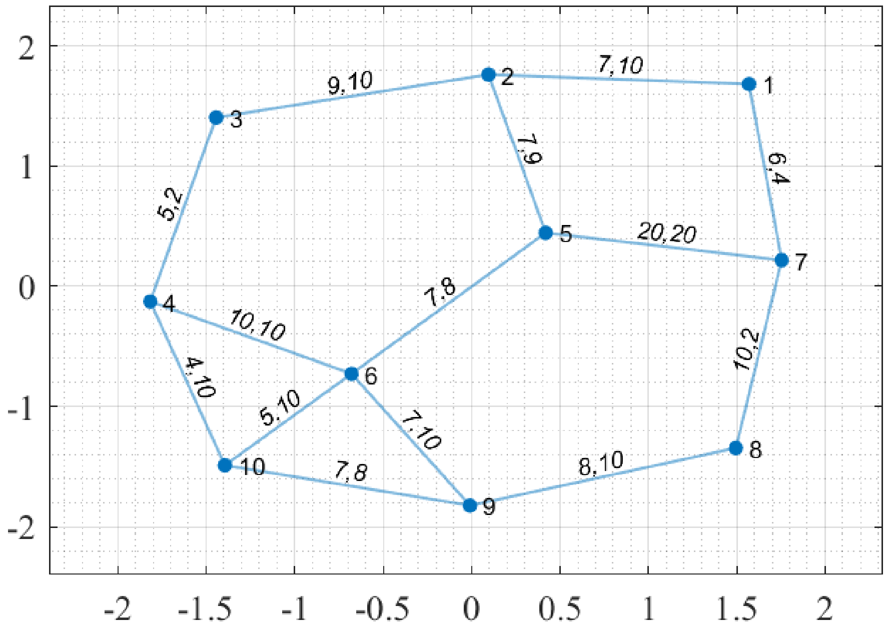

FIGURE 3.10: Bidirectional communication network with capacity constraints and link costs.

By setting the capacity of the distribution line, the maximum flow problem is remodelled to cope with congestion on the lines. For instance, Fig. 3.10 illustrates the same test graph but comprising of the link cost as well as the capacity of each link.

In Fig. 3.11, the convergence result of the optimised path from Producer 1 to Consumer 10 is shown, which is consistent with the Fig. 3.6.

However, it can be observed that, while all other links not on the optimal path converged to zero in Fig. 3.6, Fig. 3.11 provided alternate paths in cases of fault with the main optimised path. In addition, limiting the capacity installed on link 1 $\longrightarrow$ 2 from $10kWh$ to $5kWh$, it can be observed that the power flow on the link has been suppressed to $5kWh$ which is different from

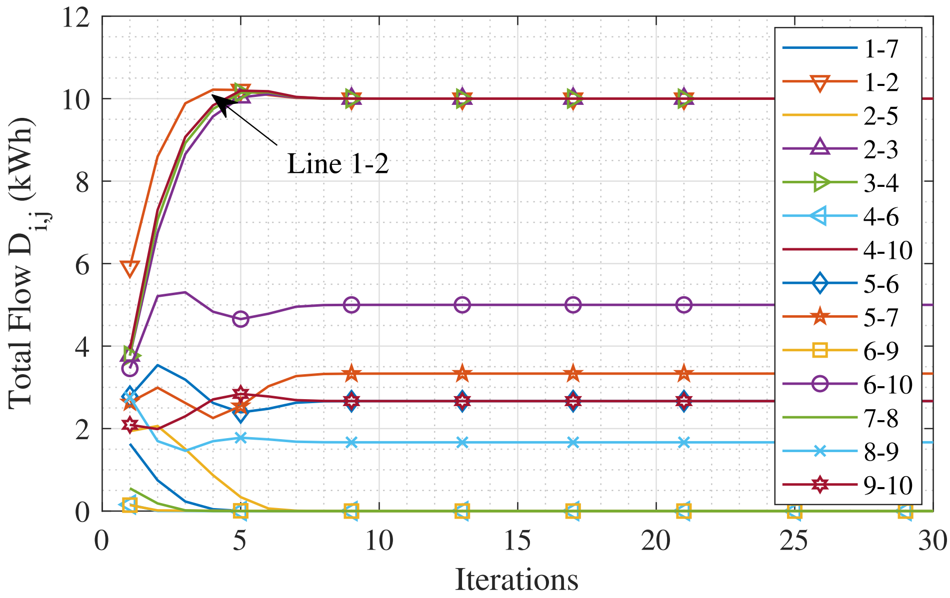

FIGURE 3.11: The demand flow on each link for optimal path for energy transfer.

Fig. 3.11 due to the restriction on the lines as shown in Fig. 3.12. This property is useful in coping with congestion on the distribution lines.

3.2.6 Comparison with Other State-of-the-Art Algorithms

Whilst this work in motivated for energy networks, it is worth noting that the solution therein can be proven for other cyber-physical networks requiring path finding algorithms. In this section, the proposed shortest path algorithm is compare to the traditional path-finding algorithms including ACO, Dijkstra [121], and IPPA (improved physarum polycephalum algorithm) [123] using different datasets shown in Table 3.1. The efficiency of the algorithm is tested over a network with random and varying topologies, with network sizes ranging from 15 to 2000 nodes [123], and link costs ranging from 1 to 100 and analysed based on the algorithm execution time. The reported probability is the probability of establishing a connection between the nodes.

3.2.6.1 Comparison Based on Execution Time

The performance of an algorithm is mostly determined by its execution time and its accuracy in solving the proposed problem. The accuracy of the

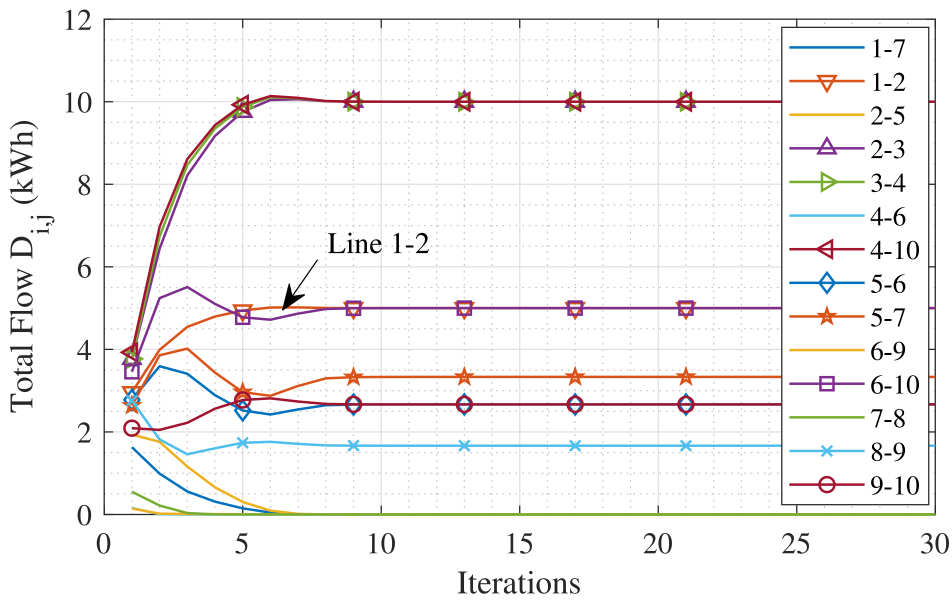

FIGURE 3.12: The demand flow on each link for optimal path for energy transfer with capacity constraints.

algorithm have been confirmed from the previously presented cases, which located the destination node utilising the least cost path and routed the demand successfully. Thus the execution time of its shortest path property is compared against other algorithms illustrated in Fig. 3.13[12], utilising the proposed algorithm for the capacitated network. This is compared against the Dijkstra, ACO and IPPA algorithm. Algorithm response time would affect network application performances, thus, it can be observed that with fewer number of nodes, the Dijkstra is faster than the developed algorithm, however as the number of nodes increased from 100, they both have similar execution time, which is of course faster than both the IPPA and the ACO algorithms. Moreover, it is worth noting that, in the Dijkstra algorithm, each link is only associated with one criterion—length—and there is no equivalent attribute like 'flow' evident in the Physarum model reacting to the change of the link cost. As a result, many classical algorithms for the cyber-physical network problem must have two separate processes/algorithms: path finding and flow optimisation. In contrast, the presented Physarum-based algorithm solves both problems simultaneously; once the link cost $A_{i,j}$ is updated, with the help of (3.4), the flow is redistributed and reallocated dynamically in the next iteration. Physarum algorithm is suitable for solving the network optimisation problems in a dynamic environment because it can utilise the computational (or

[12]Result for other algorithms have also been validated by [133].

TABLE 3.1: The test data sets for the comparison study

No. of Nodes	No. of Links	Probability
15	51	0.25
30	57	0.06
50	116	0.1
80	229	0.03
100	218	0.02
200	660	0.02
250	879	0.01
400	1592	0.01
500	1661	0.006
800	3446	0.005
1000	3324	0.005
1200	4791	0.005
1500	5614	0.003
1800	5629	0.002
2000	6393	0.002

intermediate) results in the previous iterations and respond to the changes by adjusting the flow. The scalability result of the algorithm is equally deducted from Fig. 3.13

3.3 Energy Demand Matching

Consider a case where the energy demands of a consumer in the network can be satisfied by one or more producers in the same network, however, this consumer wants to ensure that the producer with the minimum cost based on distance-metric can satisfy the required energy demand. For instance, in a network comprising of 5 consumers and 5 producers, each consumer requires a demand of $10kWh$ of energy, energy demands of Consumer A can be satisfied by Producers B, C and D, however, it is required to ensure that the producer utilising the minimum distance cost would be appropriate to satisfy the demand among the Producers B, C and D. Thus using the proposed slime mould algorithm and a Hungarian matching algorithm (also called the Kuhn-Munkres algorithm), the proposed optimised path algorithm is extended for prosumers matching in the network for a perfect match. This is to ensure that all the consumers are matched to the least distance metric producers. The Hungarian algorithm solves the maximum-weight matching (perfect matching) in a complete

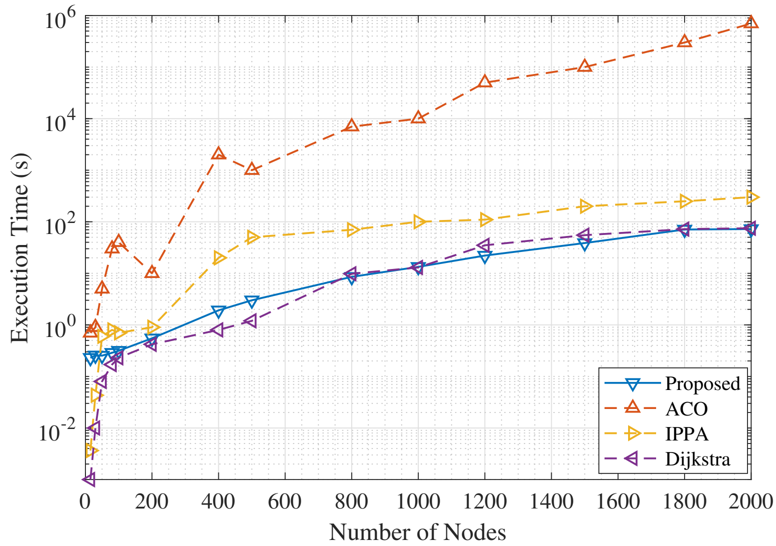

FIGURE 3.13: The comparison result of other algorithms using the execution time.

bipartite graph represented with an adjacency matrix described in (3.1). The proposed algorithm is discussed in the next section.

3.3.1 Proposed Physarum-based Prosumers Matching Algorithm

Let $\bar{M}$ be a subset of E of the graph G. If any of two links of $\bar{M}$ are disjoint in G, $\bar{M}$ is a matching of G, the two connected nodes of a link of $\bar{M}$ are matched in G. Here, n consumers' energy demands are to be satisfied by m producers in the network, considering that the consumers demands can be met by one or more producers. The aim is to ensure that at least one consumer is matched with one producer with the best distance related costs. Consider the bipartite subgraph $G^*_{N_i,N_j}$, where $N_i = \{n_{i,1}, n_{i,2}, \cdots n_{i,n}\}$, and $N_j = \{n_{j,1}, n_{j,2}, \cdots n_{j,m}\}$ denotes set of consumers and producers in the network respectively. Note that a bipartite graph is a graph that its nodes can be divided into two independent and non-empty sets.

To accommodate the matching, Algorithm 1 now becomes Algorithm 2. After the initial path optimisation, *Step 7* of Algorithm 2 starts by searching for a maximum matching in the subgraph $G^*_{N_i,N_j}$, with $G = (X \setminus Y, E)$ of bipartite sets X,Y. if one is found, the algorithm stops, else, it proceeds to the next step *Step 10*. The algorithm proceeds by initialising an empty matching (*Steps 12*

Algorithm 2: Proposed Optimised Path and Prosumers Matching Algorithm

1: ***Input:*** *The graph* $G = (V, E)$, *the distance cost* $A_{i,j}$, *total flow traffic* $D_{i,j}$, *the demand flow* $Q_{i,j}$, γ, *and the step-size,* α, *for all* $i \in N$

2: $p_j = 0$,

3: $t > 0$,

4: ***Calculate*** p_i, *according to (3.8)*

5: ***Update*** *the demand flow* $Q_{i,j} = \dfrac{D_{i,j}}{A_{i,j}} c_{i,j}(p_i - p_j)$

6: ***Update*** $D_{i,j}$ *using (3.7),* $\quad \forall j \in N$

7: ***If*** *maximum matching* $\bar{M}$ *in* $G^*_{N_i,N_j}$

8: ***End***

9: ***Else***

10: *Let* $n_i = \max\{A_{i,j} : j = 1, \cdots, n\}, n_j = 0$

11: *Let* R *be a set of nodes of size* $|\bar{M}|$ *in* $G^*_{N_i,N_j}$

12: $S := X \cap R; \bar{T} := Y \cap R$

13: $\epsilon := \min\{n_i + n_j - A_{i,j} : x_i \in X \setminus S, y_j \in Y \setminus \bar{T}\}$

14: ***Update*** n_i *and* n_j *using steps 15 & 16 respectively*

15: $\quad n_i := n_i - \epsilon$ *if* $x_i \in X \setminus S$

16: $\quad n_j := n_j + \epsilon$ *if* $y_i \in Y \setminus \bar{T}$

17: *Go to next time slot until maximum time-step is reached* *and 13)*, then search for augmenting matches in the subgraph, by flipping the matched and unmatched links along the search path (*Steps 15 and 16*).

3.3.2 Numerical Example of the Matching Algorithm

The effectiveness of the proposed algorithm is presented as follows with a One-to-Many Matching. A situation involving odd number of actors is first considered, with focus on one-to-many or many-to-one matching, i.e. a producer to many consumers, as the case arises. This reflect a real world scenario where demands of a consumer is satisfied by one or two producers, and vice versa. Utilising the average separation distances between houses in the UK **worcester** ranging from a minimum of $1m$ of a bed dwelling to $27.5m$ of a three/four storey building, the distances between the actors are determined accordingly and illustrated in Figs 3.14 and 3.15.

Fig. 3.14 reflect the case of three producers to two consumers, the producers are $N_j = \{1, 3, \&5\}$, while the consumers are $N_i = \{2, \&4\}$. It can be observed that the algorithm successfully matched the peers with the best distance cost to minimise the overall network cost. For instance, Producers 3 and 5 to Consumer 4, while Consumer's 2 demands are met by Producer 1.

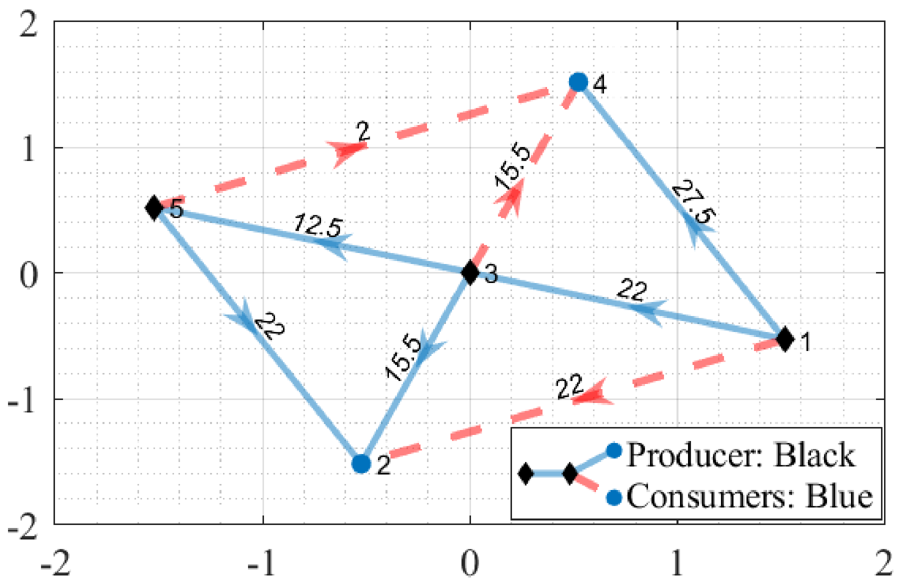

FIGURE 3.14: Bidirectional communication network showing the paired two producers to three consumers.

Similarly, Fig. 3.15 shows the result for the case of two producers $N_j = \{1, \&3\}$, to three consumers $N_i = \{2, 4, \&5\}$. Demands of Consumer 2

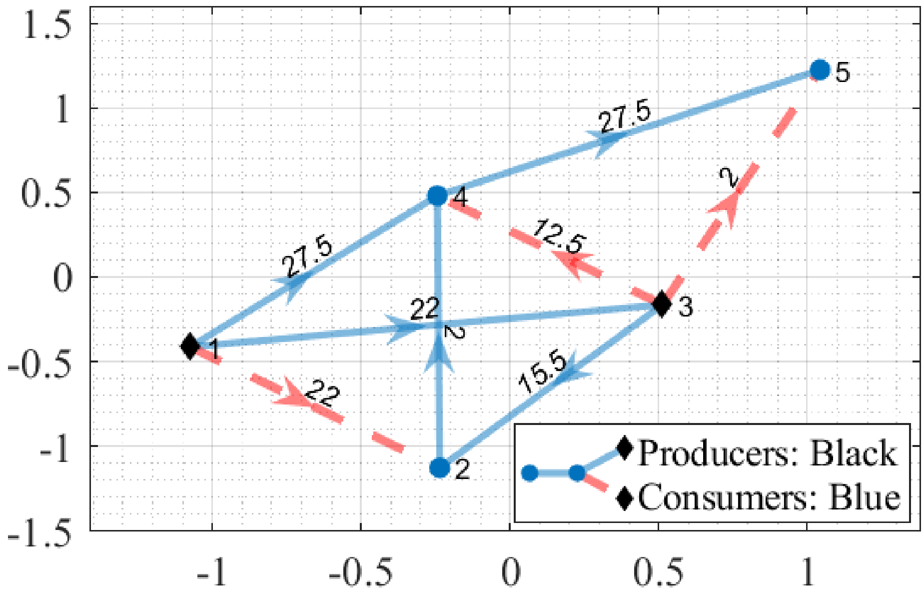

FIGURE 3.15: Bidirectional communication network showing the paired three producers to two consumers.

is satisfied by Producer 1, while demands of Consumers 4 and 5 are both supplied by Producer 3 to save costs as well as to ensure all demands are met in the network.

To further quantify the effectiveness of the proposed optimised path algorithm, Fig. 3.16 reflect the saved distance costs from the two cases previously considered.

The non-optimal path is the path the peers would have taken without the algorithm, while the optimal path is the path taken as a result of the proposed algorithm. A total of 15% cost was saved for the case of establishing an optimised path between two producers and three consumers, while 8% was saved for the case of three producers to two consumers.

3.3.3 One-to-One matching

The first numerical example considers a case of odd number of actors. Here, we focus on even number of producers and consumers in the network to produce a one-to-one matching. Using the same set numbers of prosumers from Section 3.2, but assigning 5 to be producers and 5 consumers, Fig. 3.17 is a resulting plot of the matching algorithm. The producers are

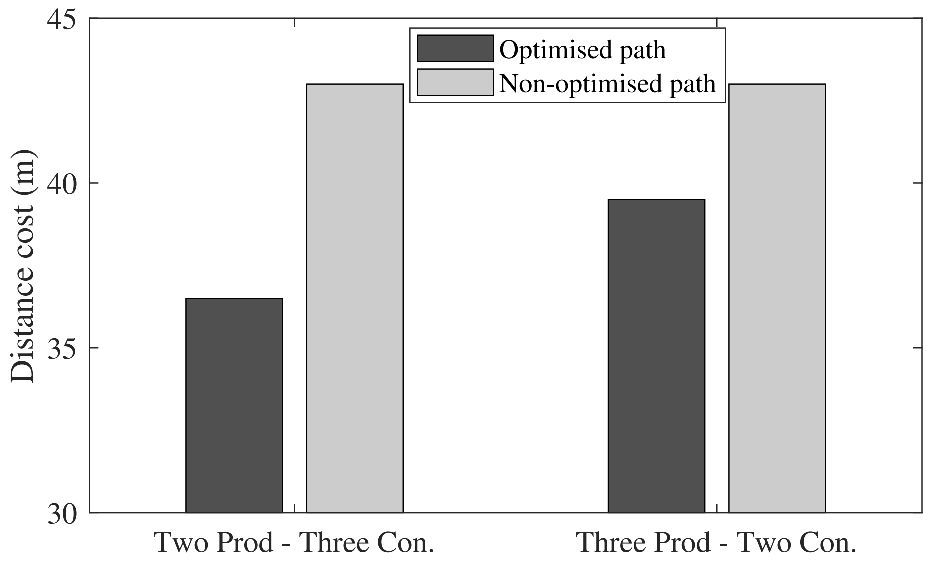

FIGURE 3.16: Cases showing the saved cost for the optimised path and non-optimised path.

$N_j = \{1, 3, 5, 7, \&9\}$, while the consumers are $N_i = \{2, 4, 6, 8, \&10\}$. It can be observed that the algorithm successfully matched the peers with the best distance cost, for instance, Producer 1 to Consumer 2, Producer 3 to Consumer 4, Producer 5 to Consumer 6, Producer 7 to Consumer 8, Producer 9 to Consumer 10. Although, when observed closely, and based solely on the link costs, Consumer 8 could have been paired with Producer 9, however if this were to be true, it would result to no pairing (or higher cost) for Consumer 10.

As established in Chapter 2 that energy lost is mostly due to long distance transmission, thus by producing power locally and matching supply and demand can minimise the losses from transportation for economic and environmental benefits. In variably, matching local energy demand, would lowers the control effort of the overall power system. Furthermore, distribution networks are vulnerable to a variety of faults, thus by providing an alternate route for power distribution, disruption to the consumers would be minimised making the electric grid more resilient. The matching algorithm presented here, considers distance as the constraints. However, in Chapter 6, the matching algorithm utilised on the P2P-ETS platform considers price and quantity of energy, as well as distance cost between the prosumers in pairing the trading peers.

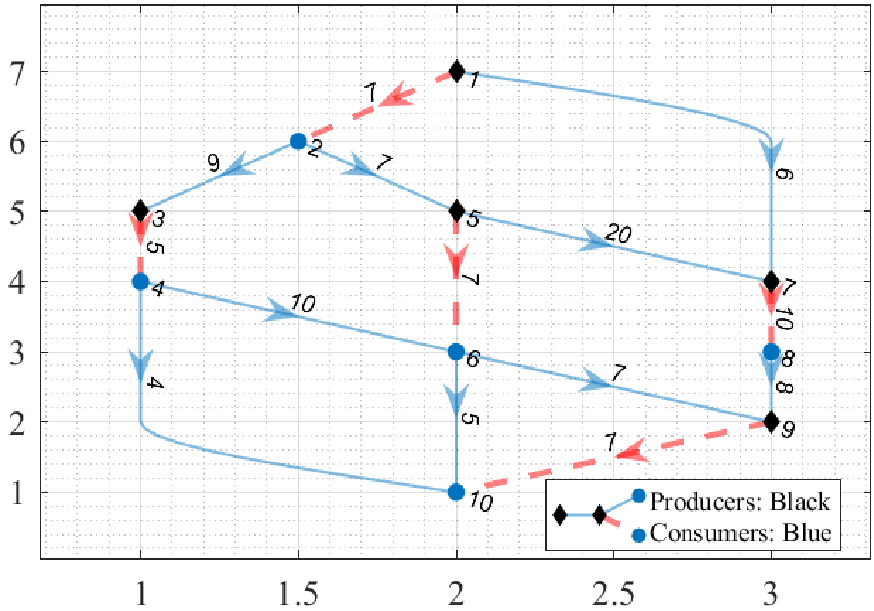

FIGURE 3.17: Bidirectional communication network showing the paired producers and consumers.

3.4 Chapter Summary

This Chapter investigated the slime mould algorithm and its properties to propose a slime mould based optimised path locality solution for energy trading peers. The proposed solution is further applied to maximum flow capacity problem in energy distribution network. Building on an extended version of the proposed slime mould algorithm, a consumer/producer pairing algorithm was developed to minimise cost based on distance related metrics. The main outcome of this study is that, with the developed algorithm, execution time in locating peers is reduced as compared to other traditional algorithms. This is highly desirable in a large network. For scalability assessment, the more the participants in the network, the longer the algorithm execution time, but this is still within MG application requirements highlighted in section 2.3. In addition, the proposed algorithm is used for capacity constraints helping to reduce congestion on the power distribution line. These results are however solely based on analysis, planning and decision-making tools to gain insights into smart grid structures so that the low level detailed design is carried out by using electrical engineering techniques. Going further, Chapter 4 discusses distributed data routing algorithm for prosumers interaction on the P2P-ETS platform.

Chapter 4

A Data Routing Algorithm for Prosumers Interactions

In chapter 2, it was established that locating whom to trade energy with is a preliminary requirement of application-specific services like data routing and energy trading. Once a particular actor[1] has been located utilising the least cost path, a distributed algorithm can be investigated for data communication among the actors in the energy network[2]. This creates a neighbourhood of producers and consumers within a given locality. Distributed energy coordination and sharing algorithms aim to minimise the energy cost of each prosumer whilst meeting the aggregate energy demand and satisfying their individual generator output capacity. These algorithms have been widely investigated for use in smart grid applications to improve reliability and efficiency of the power system, including economic dispatch problems [16][17], decentralised energy management [134][135], scheduling algorithms for smart grids [136], distributed energy trading in MGs [88][116][137][138] and distributed optimal power flow [139] etc. It was established in 2.7 that these algorithms assumed that the underlying communication network connecting the prosumers is perfect, i.e. without loss. However, for realistic deployments, algorithms' designs should take into account the suboptimal conditions of the communication network, in particular the communication links that connect the actors in the energy network. Communication network topologies may be affected by variations in signal delay, and signal loss due to environmental events or fault on the links. This has been exemplified using distributed consensus

[1]As defined in Chapter 2, actors are the entities interacting on the P2P-ETS platform consisting of consumer, producer, prosumers, DSO, etc. Where appropriate, the particular actor would be specified.

[2]Energy network is as defined with a complex network in Chapter 3.

algorithm [18] that fails to converge in the presence of prolonged communication delays.

This chapter discusses strategy for ensuring seamless communication among the connected prosumers especially in the face of imperfect communication links. A distributed routing algorithm is developed [11] and tested against unreliability and other link constraints including delay, packet loss, congestion and different network topologies. The result shows that these constraints, if not checked, will impact negatively on the communication and transactions of the energy trading entities. For instance, on the P2P-ETS platform (to be discussed in Chapter 6), after the initial matching of a producer to a consumer, a communication link is established between them. If this link is lossy or impaired, it will impact upon their effective interaction whilst trading energy.

The developed algorithm employs a multi-commodity flow optimisation (MCF) scheme that will be discussed in Section 4.1 in its formulation with the objective to minimise both the communication delay and loss of energy messages. The results show that the developed routing algorithm is robust to packet loss on the communication links, offering a 20% reduction in delay compared with a hop-by-hop adaptive link state routing algorithm. The remaining sections are organised as follows. The MCF model and its application to the energy network is presented in Section 4.1. The DAP routing algorithm and implications to P2P-ETS is presented in Section 4.2, whilst the simulation set up and results analysed in varying network configurations is discussed in Section 4.3. The main conclusions are summarised in Section 4.4.

4.1 Multi-commodity Flow Model

This section introduces the multi-commodity flow (MCF) technique utilised in Chapters 4 and 5. The MCF model has been used in transportation [140] and communication networks [141] for optimising multiple-source flow of resources in a network and now it will be extended to power networks in this thesis. MCF optimisation offers opportunity to consider the communication links whilst solving the optimisation tasks for the power network. A MCF optimisation involves multiple, concurrent, unicast flow types or commodities in G[3] and it models the average behaviour of the data

[3] G is the the graph network representing the energy network introduced in Chapter 3.

transmissions across the network using transmission resources installed on the link [140]. As the flow moves through the arcs, there is an associated cost charged according to the flow amount. The minimum cost network flow problem finds the optimal solution that minimises the cost of sending flows via the arcs, whilst ensuring that the flow demands are satisfied. If there are instances of more commodities transmitted in the network, the min-cost network flow problem is called a MCF[4] network problem. Classical MCF optimisation maximises total flow across the network, while other formulations may focus on reducing total cost in the network. The suitability of MCF to dynamic energy management has recently been assessed by [142], and applied to smart grid in [11][102][143]. The most basic MCF problem can be represented as [142]

$$\begin{aligned} &\min_{\{x_{ij,k}\}} \sum_{k \in K} \sum_{(i,j) \in E} C_{ij,k}(x_{ij,k}) \\ \text{subject to:} \quad &\text{conservation of flow constraints} \\ &\text{unit constraints} \end{aligned}$$

where E denotes the set of arcs/links in the network, $x_{ij,k}$ is the flow of commodity k on the arc (i, j) between the nodes n_i and n_j, whilst the objective function $C_{ij,k}(x_{ij,k})$ is the cost of flow in arcs, which is a convex monotonically increasing function [142]. The decision variables in this model are energy flows, observing energy flow conservation in nodes, i.e., the flow entering the node (supply) must be equal to the flow leaving the node (demand). Flows in arcs are limited by lower $l_{i,j}$ and upper $u_{i,j}$ bounds on the arcs.

4.1.1 Energy Data Coordination as a Multi-commodity Problem

Consider the IEEE five-bus system in Fig. 4.1, consisting of five-prosumers with each having some form of renewable generation unit and a control centre. The five-prosumers are connected through a communication link for information flow as illustrated. The data coordination problem among them is modeled as a MCF network optimisation to reflect differences in each prosumer's demand function. The commodity in the MCF is denoted as

[4]whilst having a single commodity in energy network, energy, MCF is used to represent different commodity or message from each of the distributed peers in the network.

energy request messages[5] for the rest of the chapter. A MCF model is

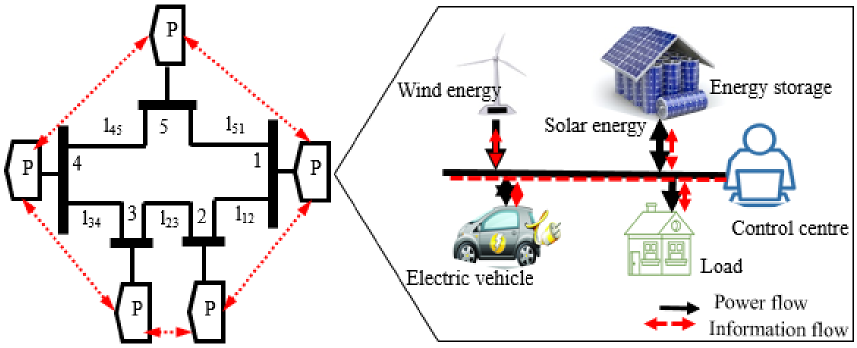

FIGURE 4.1: An example of IEEE five-bus system showing the composition and connectivity of prosumers [11]

expressed either through a link, path or destination-based formulation [140] depending on the optimisation objective. For brevity, the flow-link formulation is considered in this thesis, because the interest is in optimal message routing among the DER with an objective to minimise loss of transactional messages and communication delay.

Without loss of generality, the optimal message routing optimisation is expressed in a flow-link MCF network formulation as follows:

$$\min_{\{x_{ij,k}\}} \sum_{x_{ij,k}} \Phi_{i,j}(x_{i,j}) \tag{4.1a}$$

$$s.t: \sum_{i,j \in I_n} x_{ij,k} = \sum_{i,j \in U_n} x_{ij,k}, \qquad \forall n \in N, \quad k \in K \tag{4.1b}$$

$$\sum_{i,j} x_{ij,k} \leq c_{i,j}, \qquad \forall i,j \in E, \quad k \in K \tag{4.1c}$$

$$x_{ij,k} \geq 0, \qquad \forall i,j \in E, \quad k \in K \tag{4.1d}$$

where cost function, $\Phi(\cdot)$, associates a cost to a link, (i, j), and $x_{i,j}$, is the total traffic flow[6] on link (i, j) in the network. $x_{ij,k}$ represents the flow on link (i, j) corresponding to energy message k. I_n is the ingress link to an intermediary or destination peer n_j, while U_n is the egress link from a source or intermediary peer n_i. Equation (4.1b) is the conservation of flow constraint on energy transshipment nodes, i.e., the total message flow into a peer is equal to the total message out flow. Constraints (4.1c) suggest that the message flow in link, (i, j), must not exceed the capacity of the link $c_{i,j}$.

[5]energy request message is the data to be routed in the network which consists of energy profile, offer bids/price, etc. More details would be provided about the message frame in Section 4.3.

[6]total traffic flow is an aggregate of the individual flow of d on the link.

Constraint (4.1d) represents non-negativity of the flow traffic, $x_{ij,k}$, traversing the network.

4.2 Distributed Adaptive Primal Routing Algorithm

This section presents the distributed adaptive primal (DAP) routing algorithm [11] for the message routing problem defined in Section 4.1. It is assumed that the cost function $\Phi_{i,j}$ is differentiable and bounded because of its convexity. Thus, there exists an $L < \infty$ such that $\Phi'_{i,j}(x) \leq L \quad \forall (i,j) \in [0,\infty]_n^N$.

4.2.1 DAP Iterative Algorithm

The single point of failure problem associated with the centralised coordination algorithms motivates the research into distributed implementation, where each element can make decisions on its own, coordinated by a small amount of signaling information. Gradient algorithms provide a strong theoretical tool for creating such a distributed implementation scheme with guaranteed convergence [140], and are extended in this present chapter. Here, an iterative algorithm to the problem (4.1a) is presented.

At the t^{th} iteration, let $x_{i,j}(t)$ denote the value of the traffic rate variable $x_{i,j}$. By applying a gradient projection algorithm[7] [140], [144] to problem (4.1a), we have:

$$x_{i,j}(t+1) = \left[x_{i,j}(t) - \alpha_t \left(\sum_{x_{ij,k}} \Phi'_{i,j}(x_{i,j}(t)) - \bar{l}_{i,j} + v_k \right) \right] \quad \forall k \in K, \quad (i,j) \in E \tag{4.2}$$

where α_t is the step size at the t^{th} iterative step and $\Phi'_{i,j}$ represents the weights of the communication links which can be expressed as the gradient of the

[7] this is because of its successful application in multiple network optimisation problems. Also, they provide methods for solving bound constrained optimisation problems.

objective function as

$$\Phi'_{i,j} = \frac{\partial \phi}{\partial x_{i,j}}(x) = \sum_{(i,j)\in E} \frac{\partial \Phi_{i,j}}{\partial x_{i,j}}(x_{i,j}), \quad \forall (i,j) \in E \tag{4.3}$$

Also, from (4.2), $l_{i,j}$ is expressed as

$$\bar{l}_{i,j} = \begin{cases} 0, & if \sum_{i,j} x_{ij,k} < c_{i,j} \quad \forall (i,j) \in E & (4.4a) \\ 1, & if \sum_{i,j} x_{ij,k} \geq c_{i,j} \quad \forall (i,j) \in E. & (4.4b) \end{cases}$$

Equation (4.4) represents the link utilisation indicator for each link in the network. A link (i,j) is maximally utilised if $\bar{l}_{i,j} = 1$,. That is, if the demand traffic $x_{ij,k}$ on link i,j is $\geq c_{i,j}$ and 0 when it is $< c_{i,j}$ (link capacity). Further, from (4.2), v_k is given by the expression

$$v_k = \begin{cases} 0, & if \sum_{i,j\in I_n} x_{i,j} = \sum_{i,j\in U_n} x_{i,j} & (4.5a) \\ 1, & if \sum_{i,j\in I_n} x_{i,j} > \sum_{i,j\in U_n} x_{i,j} & (4.5b) \\ -1, & if \sum_{i,j\in I_n} x_{i,j} < \sum_{i,j\in U_n} x_{i,j}. & (4.5c) \end{cases}$$

Equation (4.5) represents the peer capacity utilisation indicator. An intermediary peer along the path of a message is considered fully utilised if $v_k = 1$, underutilised if $v_k = -1$ and balanced if $v_k = 0$. Each link monitors the value $\Phi'_{i,j}(x_{i,j})$ as a function of the traffic traversing the link and signals the updated value to each prosumer in the network. The iterative update of (4.2) can be interpreted as: the traffic on each link decreases if the source peer is underutilised or the destination peer is fully utilised, and vice versa. Similarly, the traffic on each link decreases by the gradient of the objective function while it increases or decreases according to the number of congested links on the path.

The iterative update can be formally expressed as

$$x_{i,j}(t+1) = \begin{cases} \left[x_{i,j}(t) - \alpha_t \left(\sum_{x_{i,j}} \Phi'_{i,j}(x_{i,j}(t)) - \bar{l}_{i,j} + v_k \right) \right]_+ & \quad (4.6a) \\ \qquad\qquad\qquad\qquad\qquad\qquad if i,j \in U_n & \\ \left[x_{i,j}(t) - \alpha_t \left(\sum_{x_{i,j}} \Phi'_{i,j}(x_{i,j}(t)) - \bar{l}_{i,j} - v_k \right) \right]_+ & \quad (4.6b) \\ \qquad\qquad\qquad\qquad\qquad\qquad if i,j \in I_n & \\ \left[x_{i,j}(t) - \alpha_t \left(-\bar{l}_{i,j} + v_k \right) \right]_+ \qquad otherwise. & \quad (4.6c) \end{cases}$$

This gradient projection iteration is performed by each prosumer using only locally available information, resulting in a distributed approach that does not depend on network-wide knowledge. In other words, each communication link (i, j) monitors the gradient value $\Phi'_{i,j}(x_{i,j})$, representing the flow traffic on the link as a measure to prevent maximum link utilisation. The monitored gradient value is periodically communicated to every prosumer in the network. In response, each prosumer adaptively modifies the routing according to (4.6). For instance, if it is a source prosumer, (4.6a) is executed, if it a destination prosumer (4.6b) is executed, and if it is an intermediary prosumer, (4.6c) is executed. The summary of the developed DAP routing algorithm is given in Algorithm 3.

Algorithm 3: Developed DAP Routing Algorithm

Input: $G(t) = (V, E(t))$, *the step-size,* α_t, *and link capacity,* $c_{i,j}$, *for all* $i \in N$

Output: *Cost function,* $\Phi_{i,j}(x_{i,j})$, *optimal energy demand messages,* $k_i(t)$, *and the traffic* $x_{ij,k}$ *carried on each link.*

Link's Algorithm: $t > 0$,

Compute $\Phi'_{i,j}(x_{i,j})$, *for all message values and* ***Broadcast*** $\Phi'_{i,j}(x_{i,j})$ *to the peers*

Peer's Algorithm: $t > 0$,

Receive $\Phi'_{i,j}(x_{i,j})$

Based on the role of prosumer n_i *at* t, ***update*** $x_{i,j}$ *using (4.6)*

Go to next time slot until maximum time-step is reached

4.2.2 Implication of Model Solution to P2P-ETS

In P2P, delay is a critical factor as the peers may not reach a consensus in the given period with the presence of communication delays. This would affect service delivery. For instance, if prosumer A and prosumer B in an energy network are interacting over a lossy network, a significant communication delay from either party could result in the other prosumer exchanging the transactional message with a third prosumer with a faster response. This implies that, prosumer A or B could lose the deal and related transaction profit. Amongst the leading factors that are known to affect network delay include communication link congestion. The higher the link utilisation rate[8], the longer the queuing rate and the longer it takes to deliver the messages from one prosumer to another. Thus, the convex objective function is chosen as the M/M/1 delay formulated [140][145] as

$$\sum_{x_{ij,k}} \Phi_{i,j}(x_{i,j}) = \sum_{i,j} \frac{x_{i,j}}{c_{i,j} - x_{i,j}} \tag{4.7}$$

which has a direct relationship with the link capacity utilisation. Obviously, minimising (4.7), it can be observed that (and dropping the $\sum\limits_{x_{i,j}}$ for simplicity), $\Phi'_{i,j}(x_{i,j}) = \frac{c_{i,j}}{(x_{i,j}-c_{i,j})^2}$, and that $\Phi'_{i,j}(x_{i,j}) \rightarrow \infty$, when $x_{i,j} \rightarrow c_{i,j}$. This constrains the links from operating too close to its capacity. For instance, the delay cost function assigns an increasing convex cost that tends to infinity as the traffic in each link approaches its capacity. This implies that the traffic messages will be slowed down to avoid congestion and the possible collapse or failure of the network. Here, $\Phi_{i,j}$ acts as a barrier function and link capacity constraints are enforced, penalising the solutions that violate it. Apart from using the M/M/1 delay function as a congestion indicator, the delay function is selected to form a basis of comparison with the current algorithm.

4.3 Numerical Simulation and Result Analysis

To demonstrate the performance and the convergence of the presented distributed algorithm, the optimisation simulations are performed using Java programming language [140][146]. Several network[9] topologies are

[8]for instance, when the link is operating close to its maximum capacity, resulting in link congestion.

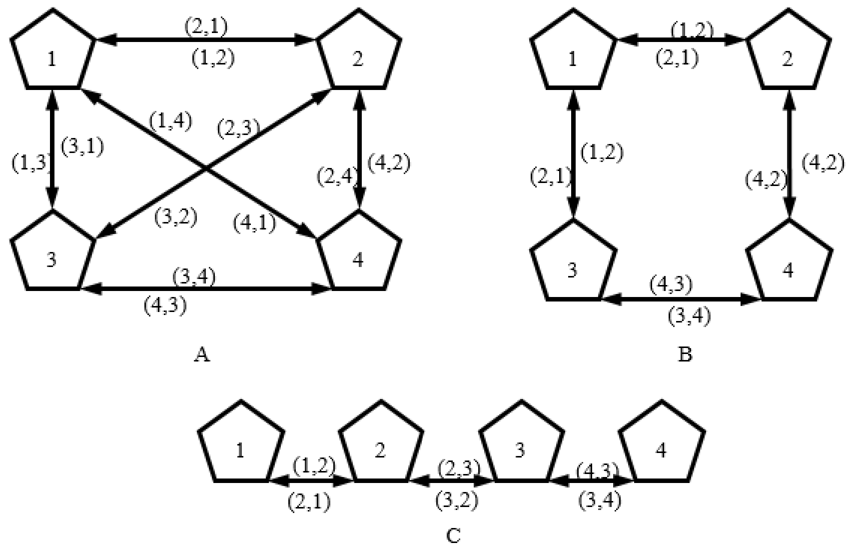

FIGURE 4.2: Bidirectional communication network used for the test cases of the developed DAP routing algorithm: **A** Full mesh. **B** Partial mesh. **C** Bus topology.

adapted from [88] as shown in Fig. 4.2.

P2P-ETS is at its infancy, thus there is no standardise communication packet framework yet. In an earlier study as part of this research to adapt the P2P communication network architecture for P2P-ETS [23], a communication packet frame structure adapted from [147] and shown in Fig. 4.3, with a message size of up to $64kB$ was proposed. The message frame structure consist of four-types of messages: peer commands to join a network, monitor/control message for energy profiling/prices, status message for notifications and stabilize message for node reporting. Thus, a set of 'energy message request' messages such as $k_1 = 45kb$, $k_2 = 35kb$, $k_3 = 35kb$, $k_4 = 40kb$, totalling $K = 155kb$ are considered for the prosumers. The 4 prosumers are respectively connected by 12, 8, and 6 links for the three topologies considered as shown in Fig. 4.2, i.e., full mesh, partial mesh and bus topologies respectively.

[9]The peers are connected in a virtual network, thus the communication network is assumed to be wireless.

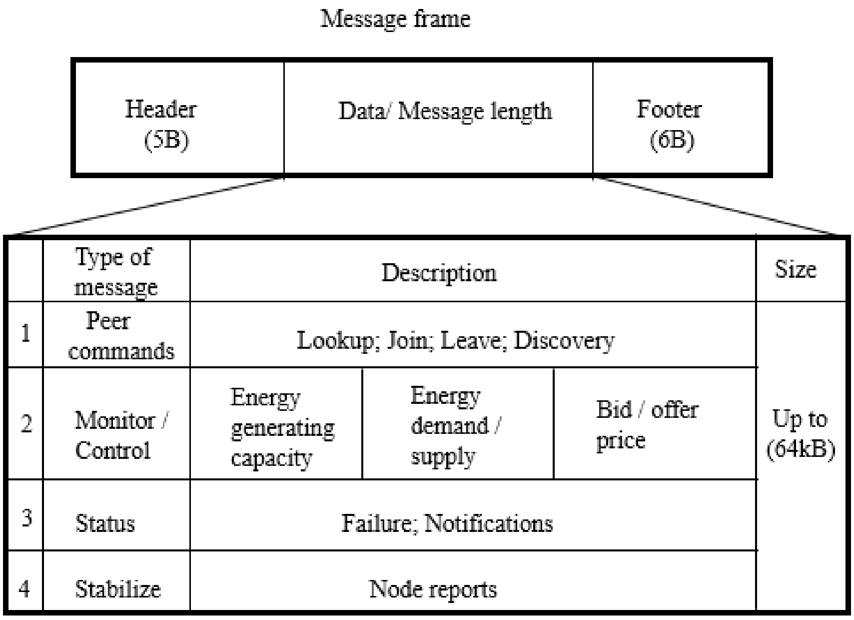

FIGURE 4.3: Communication Packet Frame Structure of Microgrid [23], [147]

4.3.1 Other Simulation Setup Parameters

The link capacities are set to a total of $C = 400kb$ equivalent to 38.8%[10] link utilisation. The step size, α_t, is set to a constant value[11] of 1 and 0.01. To consider the effect of suboptimal communication link constraints representing a typical scenario, we randomly lose some signal link update messages to verify the robustness of the algorithm to unreliable communication links arising from signal loss. Loss of signal on communication links may occur due to environmental factors or fault on the links. Thus, each communication link, (i, j), suffers a packet drop in the signal of messages of probability $p_{i,j} = 0.1$ as presented in [16]. To further reflect a typical scenario, asynchronous communication is considered in all test cases [140]. Asynchronous communication is a case where the prosumers communicate at different times and at different frequencies, which reflects a typical scenario. For the asynchronous update, the prosumers waited between $0 - 5s$ before sending their updates. The simulation parameters are summarised in Table 4.1.

[10]i.e., a total message request bits of 155kb out of total install capacity of 400kb on the link.
[11]in the subgradient optimisation method, a constant step-size to a differentiable function is guaranteed to converge to an optimal value if the choice of the step-size is small [148].

TABLE 4.1: Simulation parameters

Simulation parameter	**Value**
Demand/ message request $k \in K$	$45, 35, 35, 40(kb)$
α_t	$0.01, 1$
Signal loss probability	0.1
Total link capacity	$C = 400kb$
Asynchronous message update	$0 - 5$ time steps

4.3.2 Convergence Result for Different Network Topologies

An algorithm is considered stable when it converges to a solution in a finite amount of time [140]. This is a desirable property used to measure the algorithm performance and efficiency. The result is analysed based on the algorithm convergence time. Figs. 4.4 and 4.5 show the algorithm convergence for the full mesh and partial mesh topology respectively. The

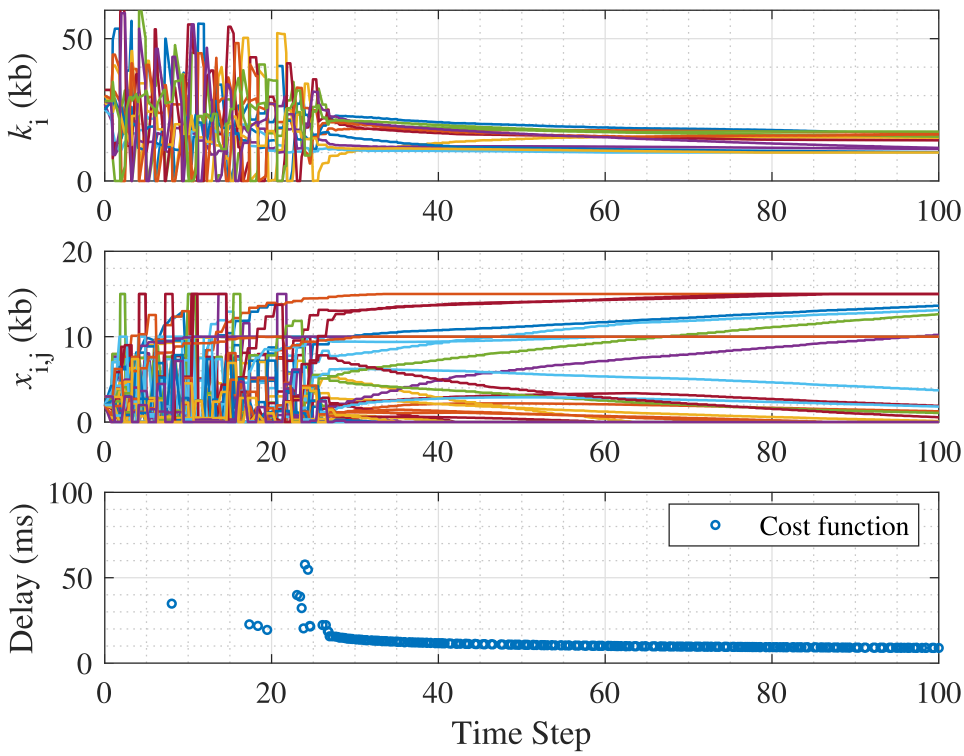

FIGURE 4.4: Full mesh topology: **Topmost plot** Convergence of the transmitted messages. **Middle plot** Convergence of the communication links. **Lower plot** The network delay function

topmost plot of Figures 4.4 and 4.5 show the convergence of the transmitted messages, the middle plots show the evolution of the total transmitted messages on each link while, the lower plot shows the evolution of the objective functions.

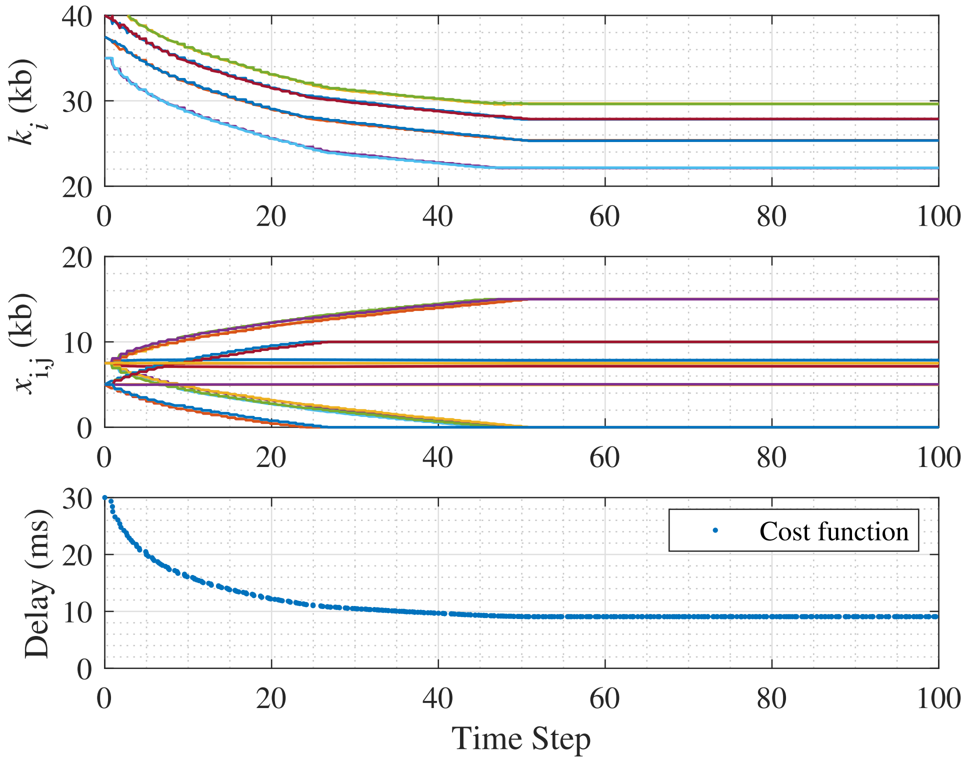

FIGURE 4.5: Half mesh topology: **(Topmost plot)** Convergence of the transmitted messages. **Middle plot** Convergence of the communication links. **Lower plot** The network delay function

A chaotic and state of instability start until the 24^{th} time step can be observed for the three variable plots of Fig. 4.4. However, a slower start was observed for the partial mesh of Fig. 4.5, before the algorithm was able to find an optimal routing solution and converge to the optimal value. It can be observed from the considered network topologies that, the mesh configuration has the lowest delay cost of 7.5ms compared with 9.7ms and 13.5ms for partial mesh and bus topology[12] respectively. This is because all the peers in the full mesh configuration are connected to every other peer, so information can be sent directly without going through an intermediary entity. However, a trade off exists in the number of consumed resources used up; full mesh has more links installed with somewhat complex configurations as the number of peers increases.

[12]the bus topology has similar plot structure to the mesh, thus for brevity, the plot graph is not included. However, the optimal delay value is reported as 13.5ms.

4.3.3 Convergence Result for Lossy Communication Links

In this section, a case of an unreliable communication network with a probability of signal loss on the communication links is considered, as well as varying the step sizes. Motivated by study [16], the probability of loss was set to 0.1 for the full mesh topology. The results are as shown in Fig. 4.6. It can be observed that the signal loss probability has little effect on the algorithm convergence compared with the ideal case which stabilizes at the $27th$ time step, but with a negligibly higher delay cost than the ideal case.

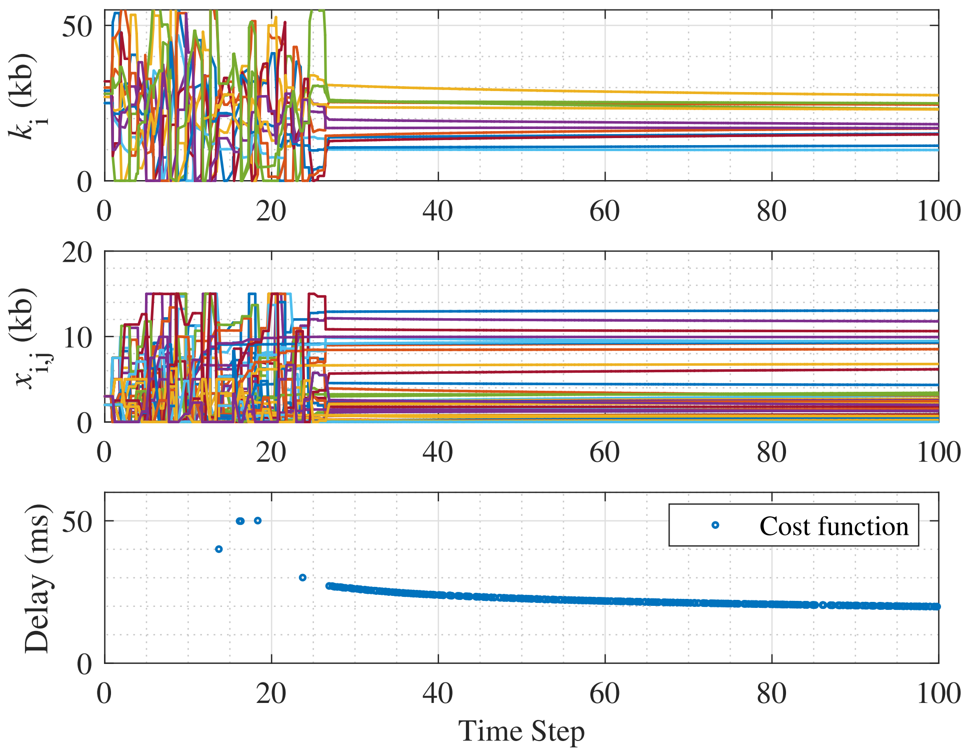

FIGURE 4.6: Full mesh topology for probability of 0.1 loss: **Topmost plot** Convergence of the transmitted messages. **Middle plot** Evolution of traffic $x_{i,j}$ on each path. **Lower plot** The objective cost delay function

4.3.4 Convergence Result for Varying Step Sizes

Research suggests that convergence for a (sub)gradient method with a differentiable function and constant step-size is guaranteed if the step size is "small enough" [148]. However, the value of the "small enough" is not defined. Thus, we vary the step size to observe the implication on the convergence time and speed. Fig. 4.7 shows the result for the network delay of different values of α_t, i.e., $\alpha_t = 1, 0.01$ and probability of signal loss of 0.1 for the 3 topologies. It can be observed that, in addition to having the lowest delay function, the full mesh topology has the lowest network delay compared with other topologies due to the direct connection between all peers in the network. However, this configuration uses more network resources leading to higher network and installation costs[13]. In addition, for a larger network, it would result in higher complexity as compared to other topologies. It can also be observed that, the network delay increases when $\alpha_t = 0.01$ compared with $\alpha_t = 1$ for the full and partial mesh, but the bus topology remains at the same level. In addition, effect of signal loss on the communication links further increases the network delay. i.e, from Fig. 4.7, the network delay for mesh when $\alpha_t = 0.01$ without loss is $450ms$, while with loss it is $520ms$. Similarly, when $\alpha_t = 1$, the network delay for mesh is $230ms$ without loss and $250ms$ with loss.

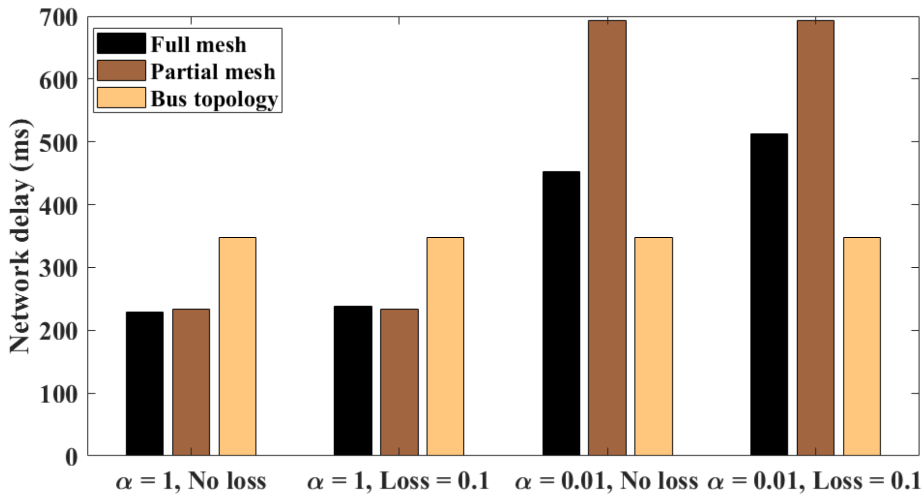

FIGURE 4.7: Total network delay for the 3 topologies for the case of probability of loss (0.1) with step sizes 1 and 0.01.

Furthermore, considering the effect of different step sizes on the algorithm convergence, α_t is varied to 1 and 0.01 to obtain Fig. 4.8. It can be observed that Fig. 4.8 corroborates the fact that with higher step sizes, convergence is faster as compared to lower step sizes. Also, the convergence is to a lower delay function value for $\alpha_t = 1$ as compared to $\alpha_t = 0.01$.

[13]this is because of the number of links installed in the network to connect all peers in a mesh.

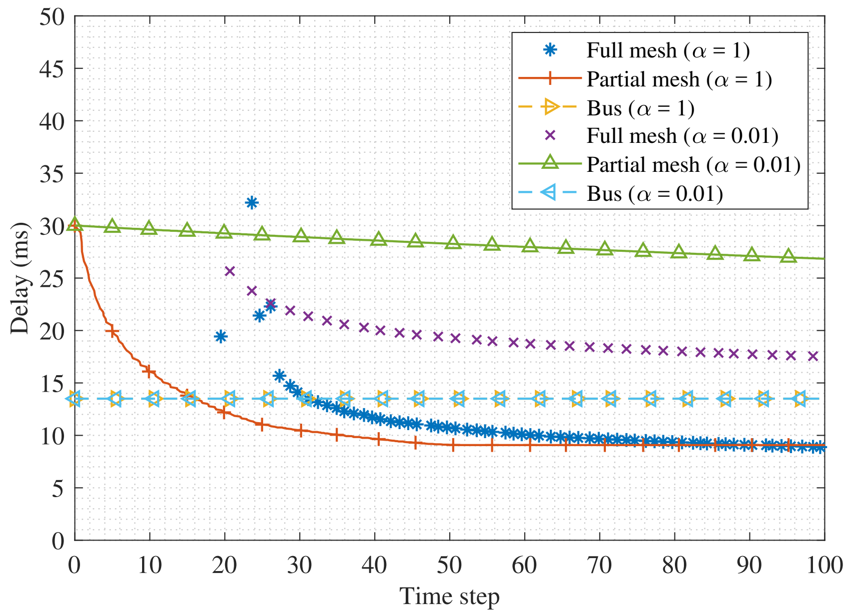

FIGURE 4.8: Convergence of the delay cost function for the 3 topologies for differing step sizes of 1 and 0.01

4.3.5 Congestion on the Communication Link

The behaviour of the three network topologies is assessed further under varying degree of average link utilisation as seen in Fig. 4.9. It is observed

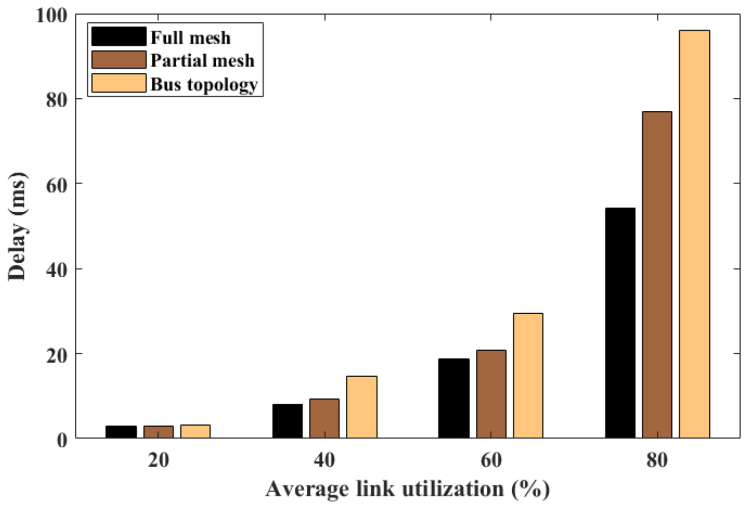

FIGURE 4.9: Time to attain optimal value for the Three Network Topologies with varying link utilisation.

that the time to attain optimal value increases as the network congestion increases. For example, when the average link utilisation is 80%, the delay function is about 94ms, compared to when the utilisation is 40% with a delay of 18ms. However, the full mesh topology outperformed the other topology configurations, which is evident from the direct connection between the peers.

Although this chapter is intended for energy network applications, it is worth noting that the algorithm can generally be applied to cyber-physical networks prone to lossy communication. In view of this, the developed DAP routing algorithm offers a significant improvement over previously proposed link state routing algorithms in the literature. In Fig. 4.10, the optimal value obtained by DAP to a hop-by-hop adaptive link state routing algorithm (HALO) [145] is compared for the full mesh topology with varying degrees of link utilisation. As it can be seen, the DAP routing

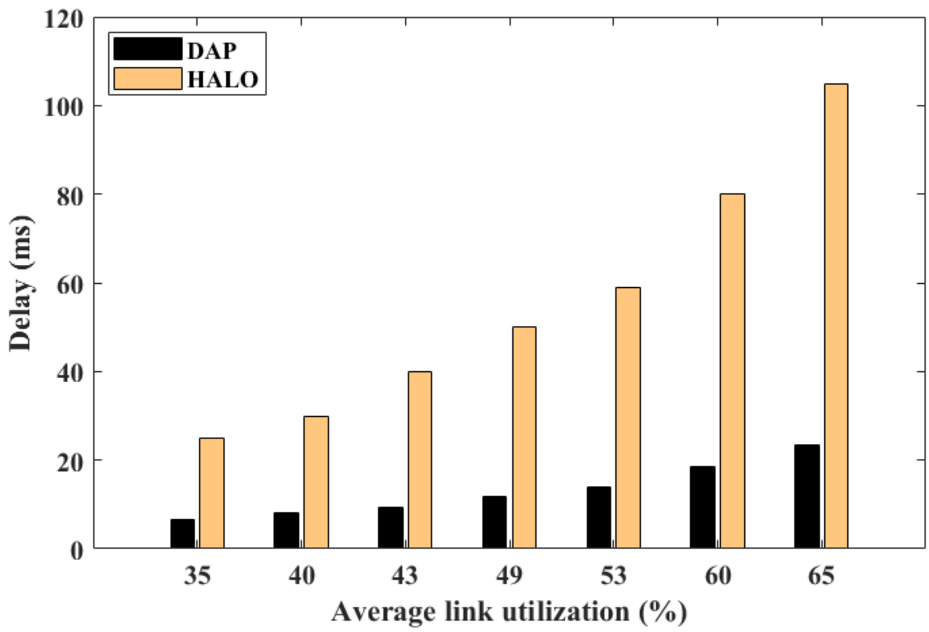

FIGURE 4.10: Time to attain optimal value for the DAP algorithm and HALO algorithm over varying link utilisation.

algorithm has lower optimal value (delay cost function) than HALO over the varying level of link capacity utilisation. This is because, at each iteration, HALO updates are calculated based on the shortest path to each destination using link state marginal costs, whereas, the DAP algorithm sets a limiting indicator on the communication link using the gradient update of the link states. This also proves the DAP algorithm significance, as the utilisation increases, the routing algorithm adaptively reroutes traffic via less congested links to realise a minimal network delay.

4.3.6 Scalability

To assess the scalability of the algorithm, the number of prosumers is increased using a typical P2P unstructured architecture, where each peer in the network is randomly connected without any particular form [23][14]. This topology reduces delay, complexity and costs (earlier reported as part of this research in [23]). Fig. 4.11 shows the resulting plot for delay cost function for $5, 10, 15$ and 30 prosumers. It can be observed that as the number of distributed prosumers increase, the delay cost function increases in almost a linear fashion, which could be $\mathcal{O}(n)$. This delay is still within an acceptable tolerance for smart grid applications [23] and within the application requirements defined in Chapter 2.

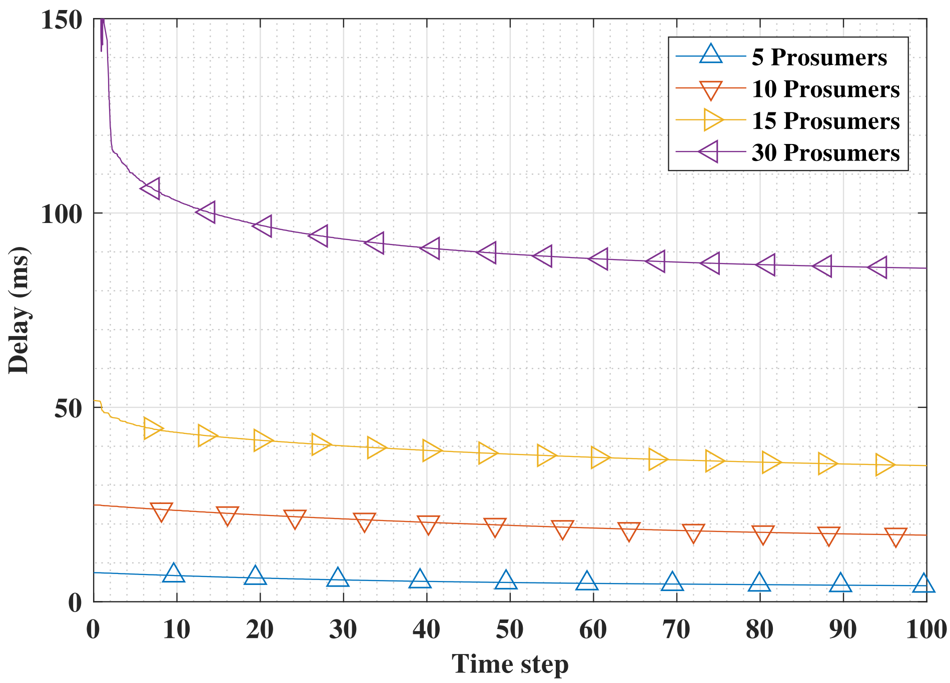

FIGURE 4.11: Delay cost function for different number of prosumers.

4.4 Chapter Summary

In this chapter, efficient message coordination among prosumers have been studied taking into consideration realistic deployment scenarios involving imperfect communication links. A DAP routing algorithm based on a MCF

[14]this topology is similar to partial mesh with random number of link connections.

network optimisation and gradient projection update is introduced, to mitigate the effects of lossy communication networks in P2P-ETS. Particularly, the problem of signal loss, delay and congestion using different topologies is addressed in the developed routing algorithm. The optimal value for the delay cost function achieved is much lower than previously proposed algorithms in the literature. The results show that the developed routing algorithm is robust to packet loss over imperfect communication links with a 20% reduction in optimal delay compared with a hop-by-hop adaptive link state routing algorithm. This shows that for a fairly sized prosumer network like 30, DAP routing algorithm recorded a delay cost of approximately 78*ms* after convergence, which is within acceptable tolerance for smart grid applications as defined in Section 2.2.

These results have a direct impact on several planning and coordination applications, especially in designing delay-sensitive networks like smart energy system by deciding the best topology and network capacity to use based on the required performance metrics and network complexity. Going further, Chapter 5 discusses resource allocation and utility maximisation of the participants on the P2P-ETS platform.

Chapter 5

Resource Allocation, Economic Dispatch and Utility Maximisation

UTILITY maximisation is of most interest to prosumers and is equally crucial for incentivising consumers to participate in P2P-ETS to realise the benefits discussed in Chapter 2. To leverage the opportunities offered by P2P-ETS, after discovering energy trading peers (Chapter 3), and routing information between them (Chapter 4), a new algorithm is actively needed to realise resource allocation, economic dispatch and utility maximisation. Economic dispatch problem (EDP) is the process in which the output from several energy generators is scheduled to meet the total connected load utilising minimal total operating cost. The future grid will have integral energy generation mix of renewable sources and a large load of EVs. This complex system necessitates the development of a decentralised approach to the resource allocation problem including energy dispatch.

This chapter solves the EDP optimisation task. The results show that by optimising individual energy generators to meet the aggregate network demand, additional costs due to energy storage may be reduced. In addition, the developed algorithm is extended to realise the global utility maximisation among market-based participants to improve overall costs and maintain fairness of all generators and demands, with further results suggesting that the entities with higher willingness to trade energy acquire more utility satisfaction. The remaining sections of this chapter are organised as follows: EDP is introduced including resource allocation and utility maximisation in Section 5.1, the problem formulation with MCF optimisation is presented in Section 5.1.1. The evaluation of the EDP model is discussed in Section 5.2. Section 5.3 discusses the resource allocation and utility maximisation among P2P energy traders as well as its numerical example and the results. Section 5.4 summarises the chapter and draws conclusions.

5.1 Economic Dispatch of Energy Resources

Consider an electrical system consisting of N generating units serving an electrical load as shown in Fig. 5.1. In this system, energy is generated from different renewable sources and with different capacities. The process in which the output from each generator is scheduled to meet the total connected load with minimal total operating cost is termed economic dispatch (ED) [149]. ED plays a critical role in the safe and stable operation of a grid system and remains an ongoing challenge in the power systems. Moreover, the integration of DER makes ED a highly complex optimisation problem with need to consider various factors like generator capacity, ramp-rate, failure rate, emission, and load profile. A decentralised approach

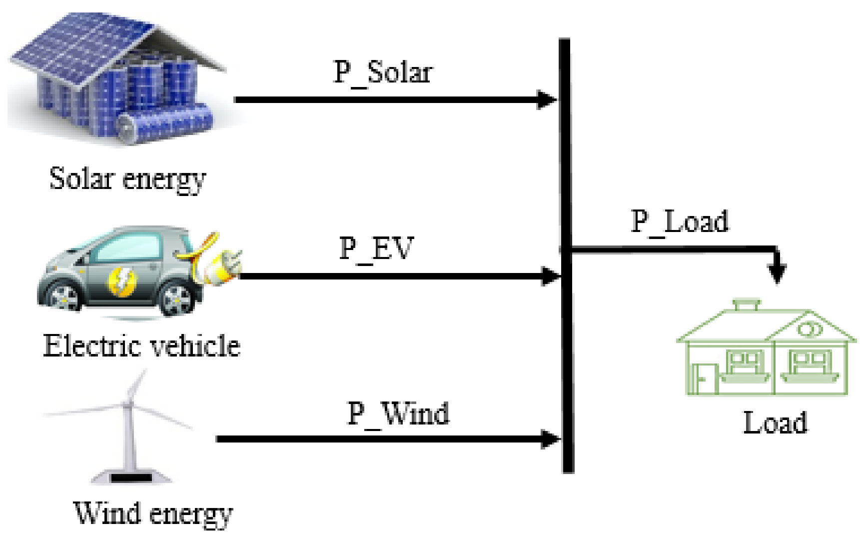

FIGURE 5.1: Distributed generating sources serving an electrical load

becomes essential for scheduling and allocation of resources in a smart grid. The uncertainty associated with renewable energy sources has made the resource allocation problems even more challenging for grid operators. Future grid will have a higher generation mix of renewable energy sources and a large load of electrical vehicles, with the possibility of bi-directional power flow, necessitating the development of a decentralised approach to the resource allocation problem for inter-node communication, decision making and energy trading. Among other qualities, such algorithms must be distributed to cater for diversity, preference and privacy of the actors.The performance limitation poised by centralised control approaches for EDP, has birthed the rise of several proposals on various distributed algorithms [16][17][18][19][20], especially for energy coordination [134], and in P2P-ETS [128][88][116]. In these algorithms, each prosumer keeps a local approximate value of its energy profile and in most cases, communicates this estimated value directly to its connected neighbour. The energy profiles of all the prosumers converge to an optimal value in a connected communication network [16]. Meanwhile, it was established in Chapter 4 that time delays and packet loss are prevalent, and if not checked, would impact negatively on the interactions and transactions of the energy trading peers. Interestingly, most of these proposed algorithms for EDP neglected the impact of communication constraints while solving the EDP.

Thus, the essence of this chapter is to model EDP utilising the MCF optimisation discussed in Section 4.1 and (sub)gradient optimisation method because of the flexibility to consider unreliable communication links whilst solving the EDP optimisation. The performance of the distributed algorithm is evaluated based on realistic network conditions relating to time-varying network delay and lossy communication links. Optimal dispatch of energy and utility maximisation is of utmost important in developing energy trading platform for prosumers.

5.1.1 Problem Formulation: System Model

Consider an energy distribution network, for example the IEEE bus-system as shown in Fig. 5.2, to which distributed energy generators are connected. Let the connectivity of these prosumers be represented using a strongly connected energy network represented by graph $G^1 = (V, E)$ of $V = \{1, 2, \cdots, N\}$ interconnected nodes, $E \subseteq V \times V$ set of bidirectional links of any (n_i, n_j) interconnected prosumers and N is the number of prosumers in the network. Note that $n_i \in N$ represents the set of energy generators and $n_j \in N$ is the set of energy consumers. The goal of each prosumer is to optimise its energy output to maximise its benefit and to

[1] introduced in Chapter 3.

collectively meet the total energy demand in the network in a distributed way.

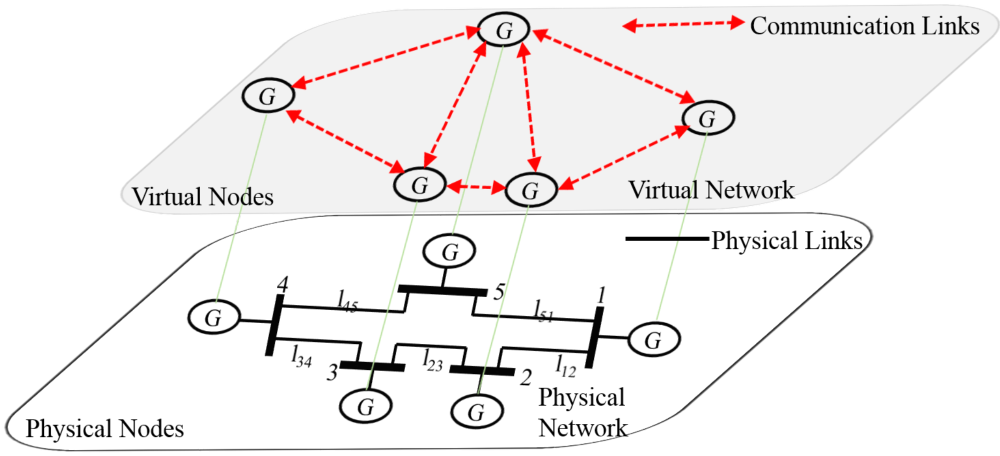

FIGURE 5.2: IEEE five-bus of energy generators in a smart grid system showing communication overlay of power network

5.1.2 Communication Network

The power network is overlayed by a communication network that coveys energy trading messages. Let the communication network be represented as a time-varying graph $G(t) = (V, E(t))$ with $E(t)$ links, where each set of links changes over time, based on the state of the communication link at time, t. A directed link from prosumer n_i to prosumer n_j is denoted by $(i, j) \in E(t)$. Each directed link $(i, j) \in E(t)$ is characterised by its upper bounds of energy trading messages through the links, $u_{i,j}$, delay, $\bar{k}_{ij}$ and signal loss probability, $f_{i,j}$ on links connecting n_i to n_j.

5.1.3 Energy Generation and Demand

For tractable solutions, we assume that the prosumers are virtually clustered using communication systems into virtual microgrids (VMG) [150]. In this case, we are interested in minimising energy generation costs and maximising social benefits within the VMG for prosumers. This problem can be approached by minimising the total aggregate energy cost by assuming small clusters of energy generators. Through clustering, energy demand can be matched with a supplier[2] within a VMG. Let

[2]as presented in Chapter 3 and would be demonstrated in Chapter 6.

$\exists\ n_j \in V$ in $E_m, \forall m = 1, \cdots, M$ where n_j represents a set of energy generators in the m^{th} cluster, each with $x_i, \forall i \in n_j$ power generation units and M is the number of VMGs in the area. The generation cost minimisation problem is formulated as

$$\min_{\{x_i\}} \sum_{i \in n_j} C_i(x_i),\ (i,j) \in E_m, m = 1, \cdots, M \tag{5.1}$$

$$\text{subject to : } \sum_{i \in n_j} x_i = D,\ (i,j) \in E_m, m = 1, \cdots, M \tag{5.1a}$$

$$x_i \geq 0,\ \forall i = 1, \cdots, n_i, n_i \in N \tag{5.1b}$$

where $C_i(\cdot)$ is the cost function of prosumer $i \in n_j$ for generating x_i units of energy. It will be assume that the cost function follows a convex function model for tractability. (5.1a) implies that the total energy generated within cluster M must be equivalent to the total energy demanded for energy conservation to hold.

5.1.4 Energy as a Multi-commodity Flow Problem

MCF optimisation has been introduced in Chapter 4. Its formulation has been extended here for EDP as

$$\min_{\{x_{ij,k}\}} \sum_{k \in K} \sum_{(i,j) \in E_m} C_{ij,k}(x_{ij,k}) \qquad \forall m = 1, \cdots, M \tag{5.2}$$

where E_m denotes the set of links between prosumers n_i and n_j in the network of m^{th} VMG, $x_{ij,k}$ is the flow of commodity k on the link between the nodes (n_i, n_j), whilst the objective function $C_{ij,k}(x_{ij,k})$ is the cost of flow in links, which is convex monotonically increasing function [142]. The decision variables in this model are energy flows $x_{ij,k}$ observing the energy flow conservation in nodes, i.e., the flow entering the node must be equal to the flow leaving the node. In addition, energy flows through the links are limited by lower and upper bounds, which translates to the maximum energy that can flow through the link at a time. For consistency, throughout the rest of the chapter, commodity is denoted as message flows from the generator unit to the demand unit.

Without loss of generality, the EDP optimisation can be represented in a MCF as;

$$\min_{\{x_{ij,k}\}} \sum_{k\in K} \sum_{(i,j)\in E_m} C_{ij,k}(x_{ij,k}) \quad \forall m = 1, \cdots, M \tag{5.3a}$$

$$\text{subject to}: \sum_{k\in K} \sum_{(i,j)\in E_m} x_{ij,k} = D \quad \forall m = 1, \cdots, M \tag{5.3b}$$

$$l_{ij,k} \le x_{ij,k} \le u_{ij,k}, \ \forall (i,j) \in A_j, m = 1, \cdots, M \tag{5.3c}$$

$$x_{ij,k} \ge 0, \quad \forall k \in K, \ \forall (i,j) \in E_m, m = 1, \cdots, M \tag{5.3d}$$

$$x_{ij,k}^{min} \le d_{ij} \le x_{ij,k}^{max}, \ \forall d_{ij} \in D, (i,j) \in E_m \tag{5.3e}$$

where d_{ij} is the virtual local demand at each bus, such that $\sum_{(i,j)\in E_m} d_{ij} = D$. Constraints (5.3b) is the conservation of energy flow constraint, i.e., the aggregate of individual energy generated output must not exceed the total energy demand in the network. Equation (5.3c) is the upper and lower bounds of flows in the links, which must not exceed the capacity of the link and (5.3d) represents non-negativity constraints, i.e, a generating unit must generate energy x_i, satisfying the lower and upper bounds of their generator capacity (5.3e).

5.1.5 Dual Lagrange Problem for EDP

To solve the minimisation over variable $x_{ij,k}$ problem of (5.3a), this section first presents its dual problem, followed by the derivation of the distributed (sub)gradient algorithm. The Lagrangian function for relaxing the flow conservation constraints of problem (5.3a) is

$$\mathcal{L}(x,\lambda) = \sum_{k\in K} \sum_{(i,j)\in A_j} C_{ij,k}(x_{ij,k}) - \sum_{k\in K} \lambda_{ij,k} D \tag{5.4}$$

$$- \sum_{k\in K} \sum_{(i,j)\in A_j} \lambda_{ij,k} x_{ij,k} \tag{5.4a}$$

$$\text{subject to}: x_{ij,k} \ge 0, \quad \forall k \in K, \ j = 1, \cdots, M \tag{5.4b}$$

$$l_{ij,k} \le x_{ij,k} \le u_{ij,k}, \forall (i,j) \in A_j, j = 1, \cdots, M \tag{5.4c}$$

$$x_{ij,k}^{min} \le d_{ij} \le x_{ij,k}^{max}, \forall d_{ij} \in D, (i,j) \in A_j \tag{5.4d}$$

where $\lambda_{ij} \ge 0$ represents the Lagrange multiplier, the incremental cost associated with the energy flow constraint. This is usually an optimal parameter that ensure the constraint conditions are not violated. A_j denotes the link between prosumers n_i and n_j in the network of m^{th} cluster. Noting constraints (5.4b) - (5.4d), (5.4) is summarised as

$$\begin{aligned}\mathcal{L}(x,\lambda) &= \sum_{k\in K}\sum_{(i,j)\in A_j} C_{ij,k}(x_{ij,k}) - \sum_{k\in K}\sum_{(i,j)\in A_j}\lambda_{ij,k}D \\ &\quad + \sum_{k\in K}\sum_{(i,j)\in A_j}\lambda_{ij,k}x_{ij,k} \quad (5.5a)\\ &= \sum_{k\in K}\sum_{(i,j)\in A_j} C_{ij,k}(x_{ij,k}) - \sum_{k\in K}\sum_{(i,j)\in A_j}\lambda_{ij,k}d_{ij,k} \\ &\quad + \sum_{k\in K}\sum_{(i,j)\in A_j}\lambda_{ij,k}x_{ij,k}\ \forall j = 1,\cdots,M \quad (5.5b)\end{aligned}$$

where $\sum_{(i,j)\in A_j} d_{ij,k} = D,\ \forall k \in K.$ The model (5.5a) can further be summarised in terms of the energy flows, thus:

$$\mathcal{L}(x,\lambda) = \sum_{k\in K}\bar{C}_{ij,k}(x_{ij,k}) + \sum_{k\in K}\lambda_{ij,k}\bar{x}_{ij,k} - \sum_{k\in K}\lambda_{ij,k}\bar{d}_{ij,k} \quad \forall j = 1,\cdots,M \tag{5.6}$$

where $\bar{C}_{ij,k}(\cdot) = \sum_{(i,j)\in A_j} C_{ij,k}(\cdot)$, $\bar{x}_{ij,k} = \sum_{(i,j)\in A_j} x_{ij,k}$ and $\bar{d}_{ij,k} = \sum_{(i,j)\in A_j} d_{ij,k}$. The argument that minimises the Lagrangian given in (5.6) by following a dual decomposition formulation and can be expressed as

$$x^{\star}_{ij,k} = \underset{x_{ij,k}\in(5.4b),(5.4c),(5.4d)}{\arg\min}\ \mathcal{L}(x,\lambda)\ s.t.\ \lambda_{ij,k} \geq 0\ \forall k \in K. \tag{5.7}$$

When $C_{ij,k}$ is strictly convex, the cost function can be investigated for the optimum (minimum) value.

The dual objective function w can be shown to enable each energy generator in the network to participate in the distributed optimisation of the energy generated in the network. This is quite scalable and efficient and also could improve the trust level in the system. Thus, the dual objective function is expressed as:

$$\begin{aligned}w(\lambda_{ij,k}) &= \min_{x_{ij,k}\geq 0}\mathcal{L}(x,\lambda_{ij,k}) \\ &= \min_{x_{ij,k}\geq 0}\sum_{k\in K}\bar{C}_{ij,k}(x_{ij,k}) + \sum_{k\in K}\lambda_{ij,k}\bar{x}_{ij,k} - \sum_{k\in K}\lambda_{ij,k}\bar{d}_{ij,k} \\ &= \sum_{k\in K}\min_{x_{ij}\geq 0}\left(\bar{C}_{ij,k}(x_{ij,k}) + \lambda_{i,j}\bar{x}_{ij,k} - \bar{\lambda}_{ij,k}d_{ij,k}\right) \quad (5.8)\end{aligned}$$

Clearly, (5.8) shows a fully $k \in K$ distribution problem that each energy generator i participates in solving. Estimating the optimal dual solution in terms of the Lagrange of the dual function problem as,

$$w^\star(\lambda^\star_{ij,k}) = \max_{\lambda_{ij,k} \geq 0} w(\lambda_{ij,k}) \tag{5.9}$$

the optimal pricing information, $\lambda^\star_{ij,k}$ is required to establish the best energy unit, $x^\star_{ij,k}$, transferred by the generator unit to the demand unit. This can be realised through an update of the pricing information in an iterative fashion which is presented in next section (5.1.6).

5.1.6 Distributed Dual-Gradient (DDG) Algorithm for EDP

Problem (5.9) is solved using the (sub)gradient method. The (sub)gradient method is a generalisation of the gradient descent, using the iterations

$$\lambda_{ij,k}(t+1) = \left[\lambda_{ij,k}(t) - \alpha_t g(t)\right]^+ \ \forall k \in K, (i,j) \in A_j \tag{5.10}$$

where α_t is the step size at time t, and $g(t)$ is a (sub)gradient to $w(\lambda_{ij,k})$ at $\lambda_{ij,k}(t)$. Note that $[r]^+ = \max(r, 0)$.

Assumption A: *Since the cost function within the dual objective function is strictly convex, then the dual function $w(\lambda_{ij,k})$ is continuously differentiable* [151].

The (sub)gradient, $g(t)$ is realised by taking the first derivative of (5.8) and setting the result equal to zero as follows

$$g(t) = \frac{\partial w(\lambda_{ij,k})}{\partial \lambda_{ij,k}} = 0 \Rightarrow -\left(\sum_{k \in K} \bar{d}_{ij,k} - \sum_{k \in K} \bar{x}_{ij,k}\right) = 0. \tag{5.11}$$

Substituting (5.11) into (5.10), a (sub)gradient update of (5.9) along each dual variable is obtained and expressed as,

$$\lambda^{(t+1)}_{ij,k} = \left[\lambda^{(t)}_{ij,k} - \alpha_t \Big(\sum_{k \in K} \bar{x}_{ij,k} - \sum_{k \in K} \bar{d}_{ij,k} \Big) \right]^+, \ \forall (i,j) \in A_j. \tag{5.12}$$

As it can be clearly seen in (5.12) that, when the demand is greater than the supply, the generators will increase the price of the excess demand energy units by α_t. For example, when $\sum_{i \in A_j} d_{ij,k} > \sum_{i \in A_j} x_{ij,k}$, the second term in (5.12) will be greater than zero thus the second term becomes positive which leads to the $[s]^+ = \max(s, 0) > 0$. The dual variables are updated bidirectionally and synchronously at discrete time $t = \{0, 1, \cdots, \infty\}$, and only neighbours can communicate. For instance, each generating unit will wait a random time before transmitting the next update of its generated output. At every time step, there is an upper bound on the optimal value of the Lagrange function (5.4), which is obtained by evaluating the dual objective function (5.9). Each link computes its (sub)gradient coordinate using the generator flow variable x_i. To reduce excess overheads and delay that could result in assigning additional scalar variables to the estimate of each generator unit at each iteration as seen in [16], the information communicated among the generators is completely distributed and limited to the incremental cost $\lambda_{ij,k}$. The novelty in this update is that, each generator ensures it uses the price as an indicator function to generate the required energy that satisfies the network demand. Each generator utilises the $\lambda_{ij,k}$ to update its generation output $x_{ij,k}$. It is worth noting that the model (5.12) reduces to a consensus problem when all the incremental cost $\lambda_{ij,k}$ are identically equal to zero, (i.e. [152]).

5.2 EDP Model Evaluation

To evaluate the performance of the developed distributed algorithm, simulations are performed using Java [140][146]. An instance of 5 prosumers adopted from study [16], which uses an IEEE 5-bus system like in Fig.5.2 is considered for comparison purpose. The generation cost function is set to a value of ±20kWh of each generator's demand[3]. This is because the objective is to optimise the generation output of each generator to satisfy the aggregate energy demand in the network. The 5 prosumers are connected by 16 links. A set of energy demands (kWh) of $d_1 = 40$, $d_2 = 30$, $d_3 = 100$, $d_4 = 40$, $d_5 = 90$ are considered. The step size, α, is set to a constant value of 1[4] for most of the cases considered.

[3]each generator produces energy in range of ±20kWh of what it consumes.

[4]in Chapter 4, it was established that, with a constant step size of 1, the network achieve lower delay, and the algorithm converges faster.

5.2.1 DDG Algorithm: without communication delay

The ideal scenario, without communication delay, is the most basic case study that exists in the literature. This is used as a starting point for testing the robustness of the proposed algorithm. The stability of an algorithm requiring the algorithm to converge to a solution in a finite amount of time is a desirable property used to measure the algorithm performance and efficiency. The result is analyzed based on the algorithm convergence time.

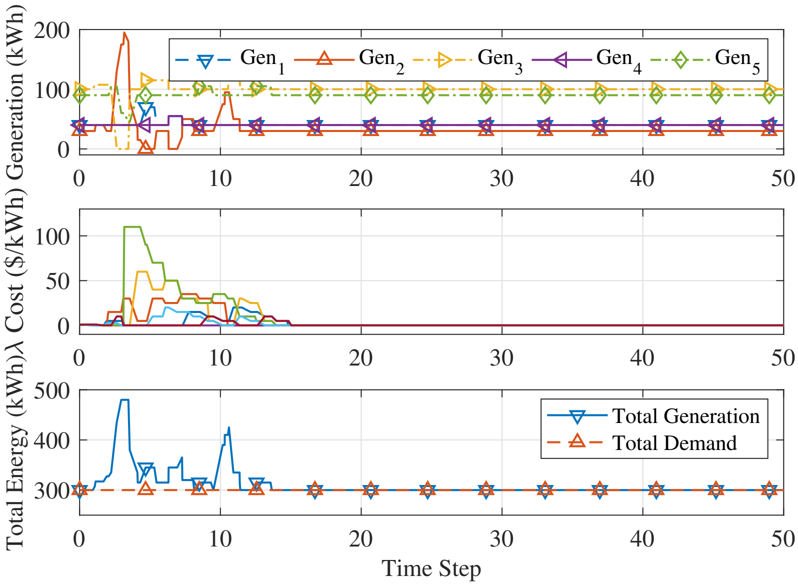

FIGURE 5.3: Results for the ideal case showing convergence of the generated energy and the incremental cost

For the ideal case without communication delay, the result is as shown in Fig. 5.3, where the middle plot shows the convergence of the incremental costs ($\lambda_{ij,k}$). The upper plot, also the generation plots, shows the evolution of the energy generated from each prosumer. The bottom plot shows the total generated energy and the total energy demanded by the prosumers. The optimal energy generated by each of the prosumers x_i, $i \in M$ is $x_1 = 40kWh, x_2 = 20kWh, x_3 = 115kWh, x_4 = 45kWh, x_5 = 80kWh$ with a total $\sum_{i=1}^{5} = 300kWh$. This shows that x_1 generated its own energy (note that the initial demand for generator 1 is $40kWh$, and the generated output is $40kWh$), while other prosumers generated below or above their energy demands to satisfy the total demanded energy in the network (an agregrate of $300kWh$). The three plots, including the incremental costs, $\lambda_{ij,k}$, settle at around 14^{th} time step, indicating about 4 communication steps $(O(n) - 2)$ for each prosumer prior to convergence.

Furthermore, from Fig. 5.3, it can be observed that at the 3rd time step, the total energy generated peaked (upper and bottom plot of Fig. 5.3). This result in an increase in the cost function (middle plot of Fig. 5.3). However, as the energy generation output descended over time to meet the demand, the incremental cost equally descended to 0. The increased cost before convergence can be interpreted as meaning that additional storage space is required for the excess energy, this increases the cost of generation. Thus the optimisation algorithm works to minimise the cost by solving the EDP problem when generated energy meets demand.

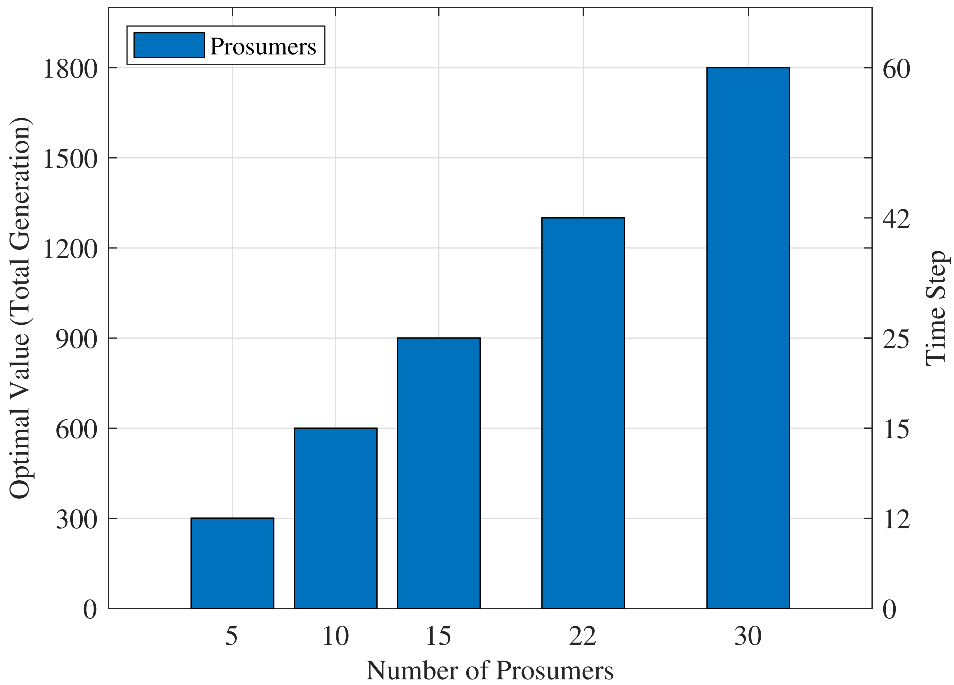

FIGURE 5.4: Scalability results showing convergence of the cost function for $5, 10, 15$ and 30 prosumers respectively

To explore the scalability of the algorithm, this research moves away from the norm of 4 prosumers [88][116] and 5 prosumers [16]. Fig. 5.4 shows the convergence of the cost function (generators) for $5, 10, 15$, and 30 prosumers with total demands set to $300kWh$, $600kWh$, $900kWh$, and $1800kWh$ respectively. As expected, the networks with 5 prosumers converges faster than the network with $10, 15$, and 30 prosumers. For instance, a network consisting of 15 prosumers attains optimal value of $900kWh$ at about the 25th time step as compared to 22 prosumers that attains $1300kWh$ optimal value at 42nd time step (Fig. 5.4). It is worth noting that during the simulation, the computation time and the number of iterations per time-step to reach the optimal value increases with increasing number of prosumers during the simulation.

In [20], a two-level incremental cost consensus (ICC) algorithm was proposed to solve the EDP in smart grid. A comparison test of the convergence time of the proposed DDG algorithm to the ICC proposed in [20] is as shown in Fig 5.5. It can be observed that the DDG converged faster than the ICC. For

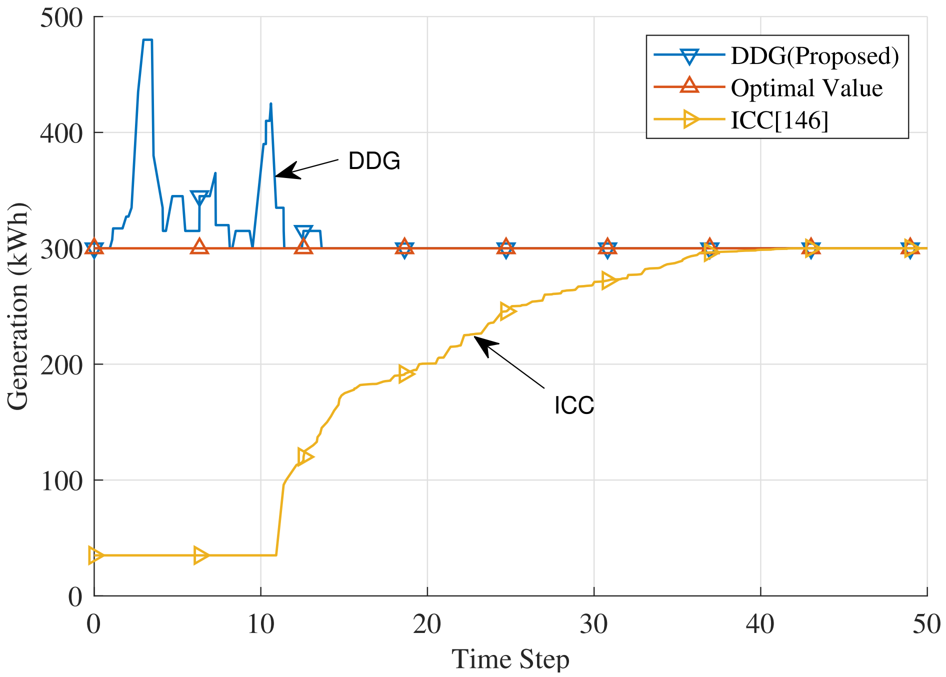

FIGURE 5.5: Comparative analysis of the convergence properties for ICC [20] and proposed DDG

instance, the total generation already matched the total demand at the 14*th* time step for DDG, whereas, the ICC converged at around 38*th* time step. The implication of this is that, while both consensus algorithms solved the EDP problem, DDG would be a better choice in large scale network.

5.2.2 Modeling the Communication Delay and Signal Loss

One of the ways to measure the robustness of an algorithm is its ability to converge in the presence of faults which could result from out of sequence delivery or loss of signalling messages. In a consensus network where all peers are minimising individual objectives to achieve a collective goal, the higher the transmission delay in such a network, the longer it takes for the peers to reach the desired agreement. Communication delay is prevalent in distributed networks, we therefore observe the robustness of DDG when the communication network is subjected to high signaling/transmission delay. In a realistic scenario, there is always a communication delay, $\bar{k}_{i,j}(t)$, on the communication link (i, j) in sending a message from prosumer, n_i, to prosumer, n_j. Similarly, there exists an end-to-end time delay, $t + \bar{k}_{i,j}(t)$, to receive a response from prosumer, n_j, by prosumer, n_i [153]. The impact of high signaling delay would result in using an outdated link cost in the gradient iteration, which would generate algorithm oscillations without reaching an optimal solution. The gradient update of (5.12) becomes:

$$\lambda_{ij,k}^{(t+\bar{k}_{i,j}(t)+1)} = \left[\lambda_{ij,k}^{(t+\bar{k}_{ij}(t))} - \alpha_t \left(\sum_{i\in A_j} x_{ij,k} - \sum_{i\in A_j} d_{ij,k}\right)\right]^+,$$
$$\forall(i,j) \in A_j, \forall j = 1,\cdots,M. \tag{5.13}$$

It has been proven in [153] that introduction of communication delay would not affect the convergence speed of the algorithm but would result in convergence to a larger neighbourhood of the optimal value. However, the choice of step size determines the algorithm convergence. A constant step size as used in this study has been proven to converge to optimal value when the objective function is differentiable [148][154].

Similarly, a probabilistic approach [16] is employed to model the signal loss on the communication link. A communication between prosumer n_i and n_j is said to be successful when the information sent by n_i is received by n_j without loss and in real-time. However, due to signal loss on the link $(i, j) \in E$, a failure vector $f_{i,j}(t)$ is introduced, where $f_i(t) = 1$ if the communication from prosumer i at iteration t is received, 0 otherwise. Thus $\omega(\lambda_{ij,k})$ in (5.8) now becomes

$$\Bigg[\sum_{(i,j)\in A_j} f_i f_j \Bigg[\sum_{i\in A_j} \min_{x_{ij}\geq 0} \bar{C}_{ij,k}(x_{ij,k}) - \bar{C}_{ji,k}(x_{ji,k})$$
$$+\lambda_{ij,k}\Bigg[(x_{ij,k} - d_{ij,k}) - (x_{ji,k} - d_{ji,k})\Bigg]\Bigg]\Bigg]^+ \forall(i,j) \in A_j, j = 1,\cdots,M. \tag{5.14}$$

However, this study only utilised the models presented in [16][153][155] to model the delay and signal loss used to examine the robustness of the DDG algorithm. Interested readers may consult the references for an extended study of the delay and probability models for the signal loss.

5.2.3 Evaluating Impact of Communication Delay

A communication delay of 10 time steps is adapted from [17] with $\alpha = 1$, and the result is as shown in Fig. 5.6. It can be observed that, each of the

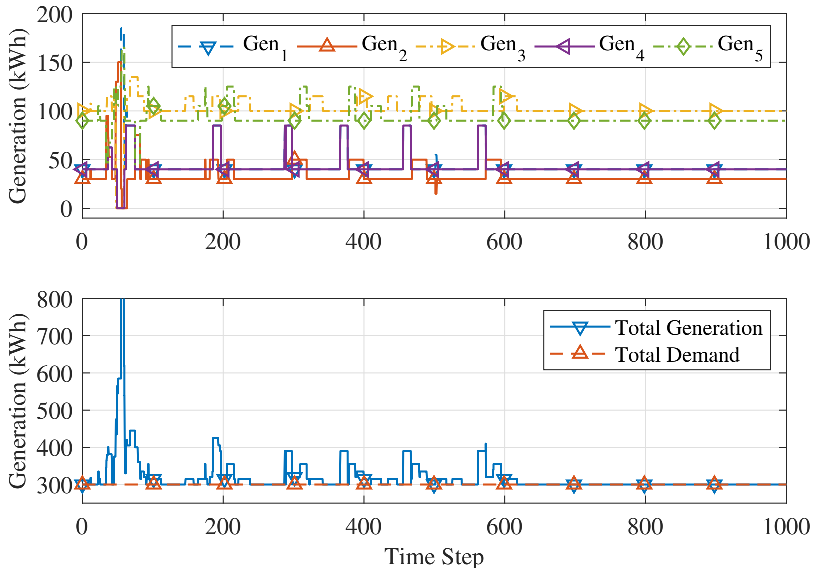

FIGURE 5.6: Results for network with communication delay showing fast convergence for the proposed DDG algorithm

variables ultimately converges to the optimal value as the ideal case, despite the signalling delays, i.e., the convergence occurred at the 610*th* time step. In comparison to the algorithm presented in [17], DDG attains its optimal solutions faster (refer to Table 5.1 for the convergence time analysis). It should also be noted that each agent in the algorithm presented in [17] holds a couple of variables that are updated and communicated at each iteration thus, adding to the communication delay. Whereas, in this study, the only communicated variable is the incremental cost signifying when to increase or reduce generation to meet the network demand. This significantly improves the communication delay leading to a faster convergence. Further, Table 5.1 compares the contribution of this chapter to the literature by detailing the cases considered and the convergence time. Unlike the work that was completed in this chapter and presented in Section 5.2.5, studies including [16][17] did not consider the cases of both signal loss and signal delay simultaneously.

TABLE 5.1: Result comparison with related works.

Description	**Ref. [17]**	**Ref. [16]**	**DDG**
Signal delay	Yes	Yes	Yes
Communication signal loss	No	Yes	Yes
Signal delay & signal loss	No	No	Yes
Asynchronous communication	No	No	Yes
Result for signaling delay case			
Algorithm convergence time step	> 900	-	610
Result for probability of signal loss case			
Algorithm convergence time step	-	> 45	18

5.2.4 Impact of Communication Signal Loss

In this section, a case of an unreliable communication network with a probability of message signaling loss on the communication links is considered. Motivated by [16] and for comparison purposes, the probability of loss was set to 0.1. The results are as shown in Fig. 5.7. It can be observed

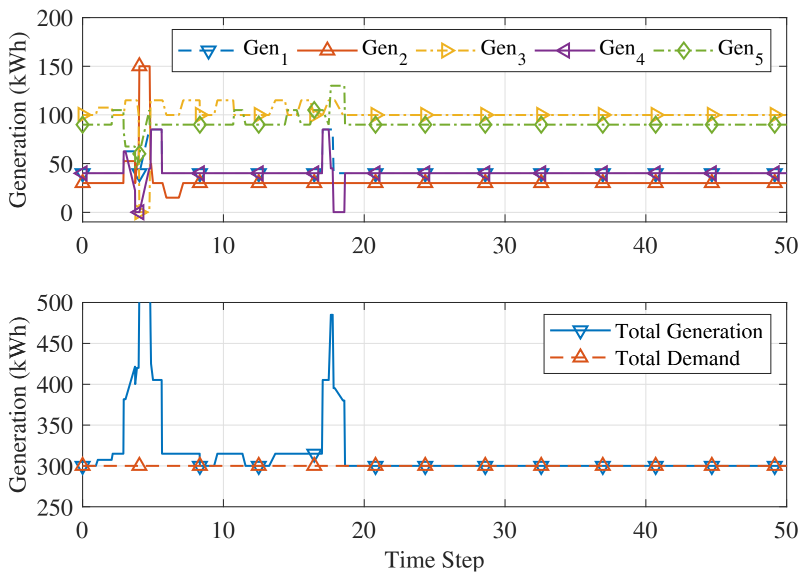

FIGURE 5.7: Results for network with probability of signal loss showing fast convergence for the proposed DDG algorithm

that the signal loss probability has negligible effect on the algorithm convergence which shows a better performance, in terms of convergence time to [16] (Table 5.1). Comparing (Fig. 5.7) and (Fig. 5.6), it can be observed that the convergence for the delay is higher than that of probability of loss. This could result from the fact that the loss is modeled as a probability function which could occur or otherwise, whereas, the delay is a constant value with high significance.

5.2.5 Impact of Communication Delay and Signal Loss

Motivated by the success of the convergence on the message with a probability of loss, a case where the communication network is both affected by signaling delay of 10 time steps and probability of loss of 0.1 is considered. Studies [16] and [17] only considered cases of delay or packet loss and not both cases simultaneously. However, the combined impact on the network is remarkably different from the effect of each variable in isolation. As shown in Fig. 5.8, the algorithm ultimately converges to the

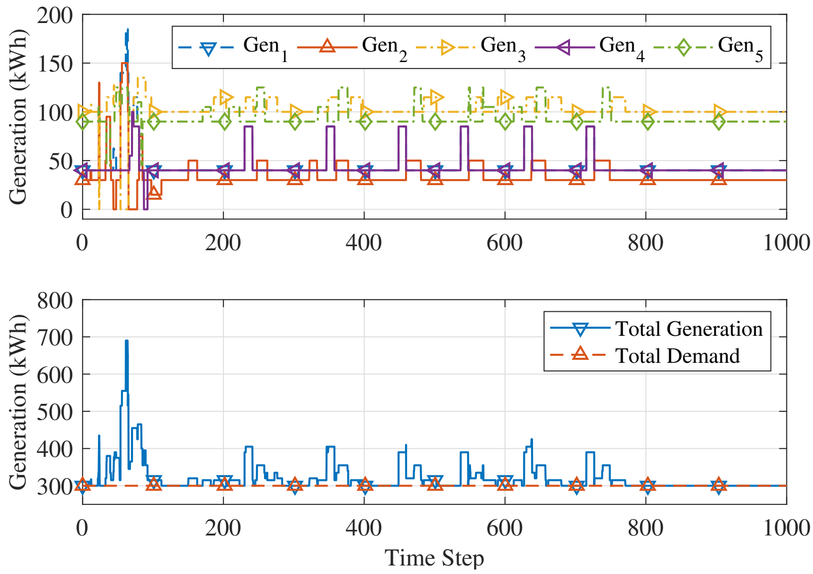

FIGURE 5.8: Results for network with both communication delay and signal loss showing fast convergence for the proposed DDG algorithm

optimal value as the ideal case. In addition, of all the cases considered, the communication delay and signal loss resulted in the highest communication link cost, which is because the prosumers synchronously transmitted their update after the communication delay, thereby oversubscribing the communication links. This observation implies that the proposed DDG algorithm is robust against signaling delay and signal loss of the underlying communication link. However, a significant level of signaling loss and delay might result in algorithm oscillations without reaching convergence. One of the future outlook of this chapter would be to extend the model by deriving the explicit relationship between delay, signal loss and algorithm stability.

It is worth noting that the robustness of the algorithm resulted from the use of MCF optimisation, as it offers opportunity to consider the communication links whilst solving the optimisation task. In addition, unreliable communication mostly result from link utilisation and congestion thus leading to signal drop and signal delay [11]. It can be noted, that by utilising the MCF optimisation, the research has already set a limit to the maximum allowed traffic based on the capacity of the link at the time, thus reducing the probability of maximum utilisation and congestion, and thus signal drop.

5.3 Resource Allocation for P2P-ETS

An energy market is further considered comprising energy generators/producers and energy consumers/loads. The general fairness utility model is given by: $U(x_i) = \frac{x_i^{1-\alpha}}{1-\alpha} \quad \forall i \in n_j, \ j = 1, \cdots, M$. For weighted utility model, the utility of a producer can be rewritten as

$$U(x_i) = \omega_i \frac{x_i^{1-\alpha}}{1-\alpha} \forall i \in n_j, \ j = 1, \cdots, M \tag{5.15}$$

where α is the fairness parameter and ω_i is the weight associated with utility of actor i. Let $\alpha \to 1$, then using L'Hopital's rule[5][156], we find that

$$\lim_{\alpha \to 1} \frac{x_i^{1-\alpha}}{1-\alpha} = \log(x_i) \quad \forall i \in n_j, \ j = 1, \cdots, M. \tag{5.16}$$

By using (5.16) and (5.15), we can rewrite the utility model as

$$U(X_i) = \omega_i \log(x_i), \forall i \in n_j, \ j = 1, \cdots, M. \tag{5.17}$$

Suppose that $x_i = 0, \forall i \in n_j$, then $log(x_i) = -\infty$. To overcome this problem, a constant $\theta \geq 1$ is introduced so that the utility becomes $U(X_i) = \omega_i \log(x_i + \theta_i), \forall i \in n_j$. Now, for $|n_j|$ actors, where $|\cdot|$ represents the cardinality of set n_j, our interest is to maximise the resources allocated to a actor over a finite link capacity. This is approached by maximising the utility of each actor subject to a capacity constraint and considering the optimisation variable as the energy resources traded over the link. In that

[5] used to solve differentiable function with indeterminate form by differentiating the numerator and the denomerator, then taking the limit.

case, the optimisation problem becomes:

$$\max_{\{x_i\} i \in n_j} \sum_{i \in n_j} U_i(x_i)$$

$$\text{subject to : } \sum_{i:\ell \in i} x_i \leq c_\ell \quad \forall \ell \in n_j$$

$$x_i \geq 0, \quad \forall i \in A_j, \; \forall j = 1, \cdots, M \tag{5.18}$$

where c_ℓ is the capacity of link ℓ and A_j represents the set of all links in the network. Fig. 5.9 demonstrates the utility function of five prosumers in a

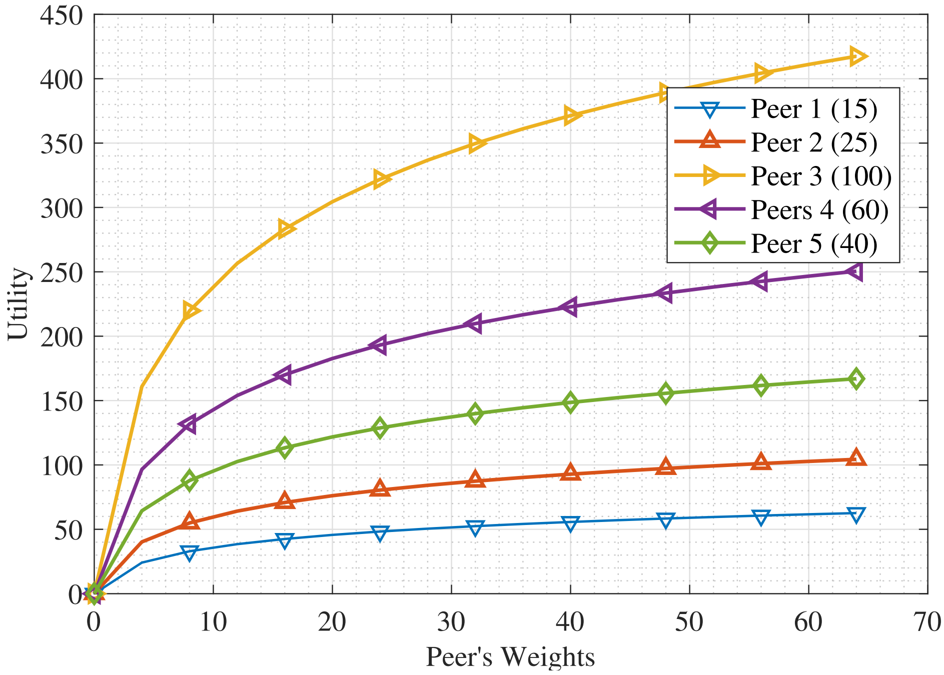

FIGURE 5.9: Relationship between the utility function and varying weights of the peers.

network with different weights, w_i in brackets. The graph shows that the utility increases for varying increasing weights of the energy traders. Physically, the weights may be interpreted in relation to willingness to trade energy with other peers. Producers with higher willingness to trade energy achieve higher utility than other prosumers with little or no willingness.

5.3.1 Optimal Resource Allocation

Invariably, if utility is proportional to willingness, higher energy flow will be experienced in the network, thus resources must be fairly and optimally allocated to each actor so as not to starve other prosumers in the network. Throughout this study, we consider fairness parameter $\alpha = 1$ as shown in (5.15). Next, we consider realising the optimal resources that can be allocated to link $i \in n_j, \forall j = 1, \cdots, M$ considering capacity $c_\ell, \forall \ell \in A_j$. By taking the Lagrangian of (5.18), we express

$$\mathcal{F}(x,\eta) = \sum_{i\in n_j} U_i(x_i) - \big(\sum_{i\in n_j} x_i\eta_i - \sum_{i\in n_j} \eta_i c_\ell \big) \ \forall \ell \in A_j \tag{5.19}$$

where $x = (x_1, x_2, \cdots, x_n)$, $\eta = (\eta_1, \eta_2, \cdots, \eta_n)$ and $n = |n_j|$. By taking the first derivative of (5.19) with respect to x_i and setting the result equal to zero, this is derived:

$$\begin{aligned}
\frac{\partial \mathcal{F}(x_i,\eta_i)}{\delta x_i} &= 0 \Rightarrow \sum_{i\in n_j} \frac{\omega_i}{x_i+\theta_i} - \sum_{i\in n_j} \eta_i = 0 \\
\Rightarrow \sum_{i\in n_j} x_i &= \frac{\sum_{i\in n_j}\omega_i - \sum_{i\in n_j}\eta_i\theta_i}{\sum_{i\in n_j}\eta_i} \\
\Rightarrow x_i^* &= \frac{\omega_i - \eta_i\theta_i}{\eta_i} \quad \forall i \in n_j,\ j = 1, \cdots, M.
\end{aligned} \tag{5.20}$$

From (5.20), the optimal resource allocation x_i^* $\forall i \in n_j,\ j = 1, \cdots, M$ depends on the congestion price η_i and the number of actors on the link. For example, to reduce the resource flow on the link due to actor i, implies increasing the congestion price η_i. Similarly, to increase the resource flow due to prosumer i implies reducing the network congestion price η_i. In addition, from (5.20), increasing the congestion price will be useful in controlling congestion in the network as lower amount of data will be sent by each actor over the link ℓ.

5.3.2 Social Welfare Maximisation

Using the foregoing utility function, this section introduces a social welfare maximisation objective to improve on the overall costs and maintain fairness for all generators and demands. Let J represent the total social welfare comprising of the energy generators $W_i(.), \forall i \in n_j$ and demand units $W_j(.), \forall j = 1, \cdots, M$, $\bar{p}$ is the price of electricity

$$\underset{\{x_i, d_j\}}{\textbf{maximise}}\ J = \left[\sum_{i \in M} W_i(x_i, \bar{p}_i) + \sum_{j \in M} W_j(d_j, \bar{p}_j)\right] \tag{5.21a}$$

$$\text{subject to}: \sum_{i \in M} x_i = \sum_{j \in M} d_j \tag{5.21b}$$

$$x_i^{min} \le x_i \le x_i^{max}, \quad i \in M \tag{5.21c}$$

$$d_j^{min} \le d_j \le d_j^{max}, \quad j \in M. \tag{5.21d}$$

Constraints (5.21b) is the conservation of energy flow constraint while the operational constraints (5.21a) and (5.21d) represents the lower and upper bounds of energy generation and consumption respectively, which are further defined as follows:

1. **Generator welfare**: Let $\bar{p}_i x_i, \forall i \in n_j, j = 1, \cdots, M$ represent the revenue that generator i receives from selling x_i units of energy with selling price $\bar{p}_i$, then the social welfare of the generator i can be expressed as:

$$W_i(x_i, \bar{p}_i) = \bar{p}_i x_i - C_i(x_i) \tag{5.22}$$

   where $C_i(x_i)$ is the cost incurred by i to generate x_i units of energy. We model the cost as a convex quadratic function of the form:

$$C_i(x_i) = \frac{1}{2} a_i x_i^2 + b_i x_i + c_i \tag{5.23}$$

   where $a_i \ge 0$, $b_i > 0$ and $c_i = 1, \forall i \in n_j, j = 1, \cdots, M$ are the cost parameters.

2. **Consumer welfare**: For the consumer side, the social welfare is the difference between the utility it derives and cost of procuring $x_j, \forall j = 1, \cdots, M$ units of energy.

$$W_j(d_j, \bar{p}_j) = U_j(d_j) - \bar{p}_j x_j, \quad \forall j = 1, \cdots, M \tag{5.24}$$

   where $U_j(d_j)$ is the utility function that defines the amount of satisfaction that consumer j receives from demanding d_j units of energy and $\bar{p}_j$ is the payment made for d_j. As shown in (5.17), the utility function of the consumer is continuously differentiable and non-decreasing.

Substituting (5.24) and (5.22) for the generator and consumer welfare in (5.21a), respectively, the total social welfare of the prosumer makes the optimisation problem to become

$$\underset{\{x_i,d_j\}}{\textbf{maximise}}\ J = \sum_{j\in M} U_j(d_j) - \sum_{i\in M} C_i(x_i) \tag{5.25a}$$

$$\text{subject to}: \sum_{i\in M} d_j \leq \sum_{j\in M} x_i \tag{5.25b}$$

$$x_i^{min} \leq x_i \leq x_i^{max}, \quad i \in M. \tag{5.25c}$$

Notice that in (5.25a), the power balance criteria earlier defined in (5.3b) enabled $(\sum_{i\in n_j} \bar{p}_i x_i - \sum_{j\in M} \bar{p}_j d_j)$ to be eliminated. Due to the concave properties of (5.25a), the model in (5.25) is a concave maximisation problem and can be solved using convex programming techniques. To achieve this, we start by formulating the Lagrangian of problem (5.25) as follows

$$\mathcal{J}(d_j, x_i, \lambda_{i,j}) = \sum_{j\in M} U_j(d_j) - \sum_{i\in M} C_i(x_i) - \lambda_{i,j}\Big(\sum_{j\in M} d_j - \sum_{i\in M} x_i\Big) \tag{5.26}$$

In terms of generators and consumers, problem (5.26) can be decomposed and solved in a distributed fashion as follows

$$\mathcal{J}(d,\lambda) = \sum_{j\in M} U_j(d_j) - \sum_{j\in M} d_j\lambda_{i,j} \tag{5.27a}$$

$$\mathcal{J}(x,\lambda) = \sum_{i\in M} \lambda_{i,j}x_i - \sum_{i\in M} C_i(x_i) \tag{5.27b}$$

by taking the first derivatives of (5.27a) and (5.27b) with respect to d_j and x_i, and 5.26 with respect to $\lambda_{i,j}$, respectively, and setting the result equal to zero. In that case, the optimal flow variables can be expressed as:

$$\frac{\partial \mathcal{J}(d,\lambda)}{\partial d} = 0 \Rightarrow d_j^* = \frac{\omega_j - \lambda_{i,j}}{\lambda_{i,j}} \tag{5.28a}$$

$$\frac{\partial \mathcal{J}(x,\lambda)}{\partial x} = 0 \Rightarrow x_i^* = \frac{\lambda_{i,j} - b_i}{a_i} \tag{5.28b}$$

$$\frac{\partial \mathcal{J}}{\partial \lambda} = 0 \Rightarrow \lambda_i^* = -\sum_j d_j + \sum_i x_i. \tag{5.28c}$$

From (5.28a), the demand is inversely proportional to the price. In other words, consumers will watch the prices of energy to buy more at low price or buy lesser energy units at higher energy price. From the generator side in (5.28b), they are motivated to supply more, linearly, at higher prices and vice versa. From (5.28c), the update function is expressed as

$$\lambda(n+1) = \left[0, \lambda(n) - \alpha\left(\sum_i x_i - \sum_j d_j\right)\right]. \tag{5.29}$$

5.3.3 Numerical Example of Optimal Resource Allocation and Social Welfare

Given a linear network shown in Fig. 5.10, utilising the utility model and the optimisation problem of (5.18), with constraints as shown. The results shown in Fig. 5.11 demonstrate the optimal data flow rates under the α-fairness condition, which indicates that Peer 3 has the highest utility function.

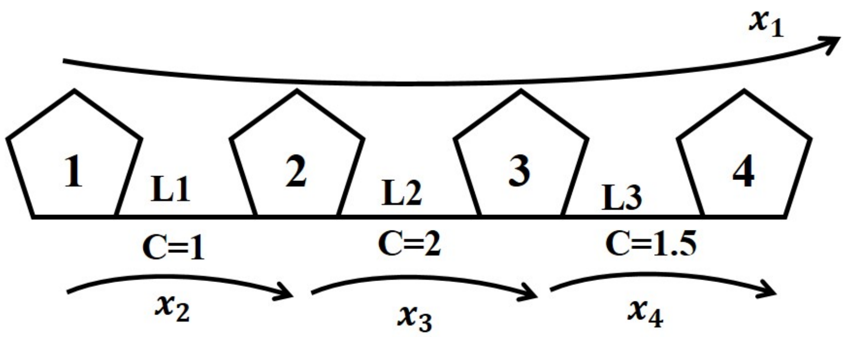

FIGURE 5.10: An example of a linear network topology for resource allocation demonstration

Solving for the optimal demand flow yields Fig. 5.12, which show that the Peers 2, 3 and 4 have more social welfare than Peer 1. In addition, Fig. 5.13 shows a typical run over a 24 hour period depicting the relationship with energy demands and supply in the network. The results reflect reduction in quantity of energy demanded when the supply is at the highest price, obeying the law of demand and supply. However, the ratio of producers to consumers in the network affects the price paid for the energy bought or sold as shown in Fig 5.13. Take for instance, at 40s, with 20 producers and 8 consumers, the total supply is 2.2kwh and demand is 9kWh. Whereas, with 10 producers and 20 consumers, the total supply is 3.6kWh, and demand is 7kWh.

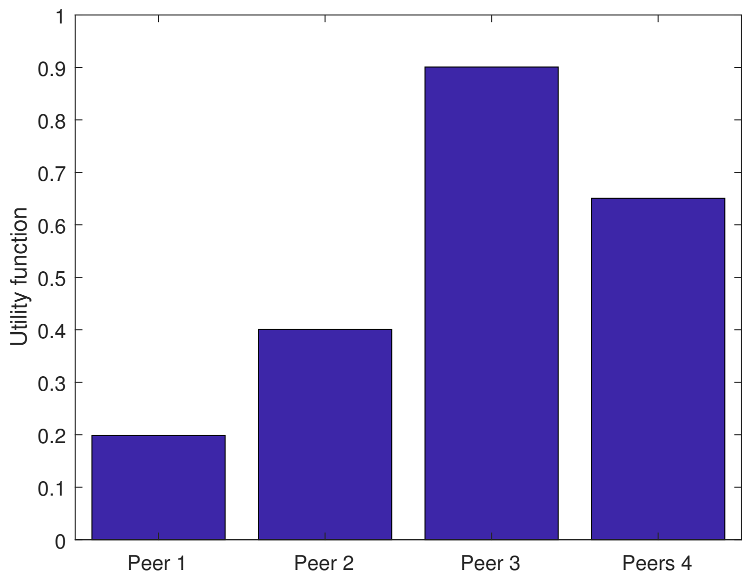

FIGURE 5.11: Optimal data flow rates under α-fairness condition for the peers in the network

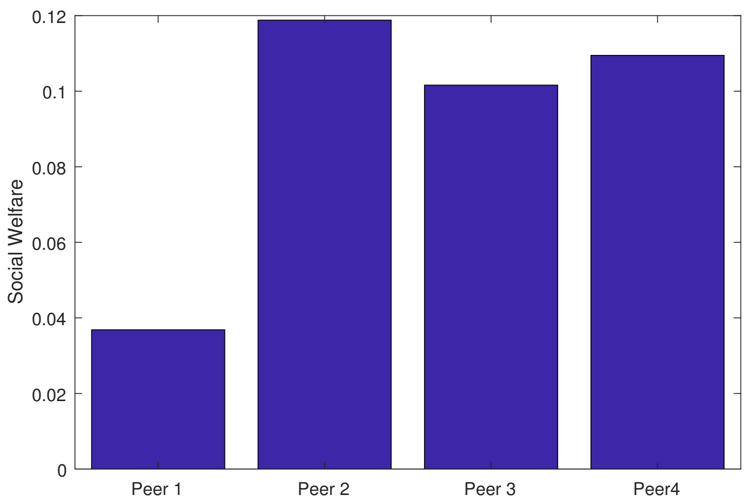

FIGURE 5.12: Optimal social welfare under α-fairness condition for the peers in the network

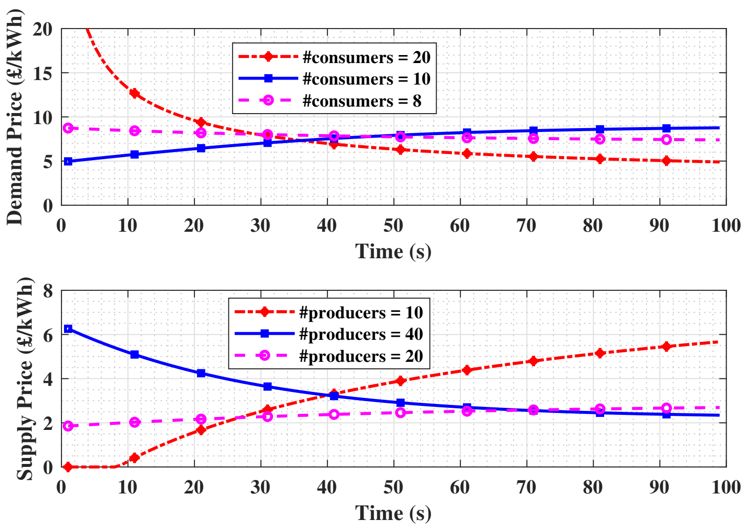

FIGURE 5.13: Optimal social welfare for different numbers of producers and consumers in the network

5.4 Chapter Summary

This chapter presented a DDG algorithm based on MCF and a dual-(sub)gradient method for the distributed EDP application. Specifically, the presented model is evaluated in the case of an unreliable communication network, subject to signal loss probability, message delay, and asynchronous communication of prosumers. The model converges faster than other previously proposed algorithms in the literature. The model is further extended to realise the global utility maximisation among market-based participants to improve overall costs and maintain fairness of all generators and demands. Results show reduction in quantity demanded when supply is at the highest price, but the price paid is dependent on the ratio of producers to consumers in the network.

While this chapter has been motivated by the energy network for optimal allocation of resources, the solution developed herein can be used to address other networked cyber-physical systems subject to sub-optimal communication network. Bringing it all together, Chapter 6 discusses the P2P-ETS platform with further analysis on the effect of the ratio of producers to consumers on the P2P-ETS platform.

Chapter 6

Peer-to-Peer Energy Trading and Sharing Platform

THIS chapter presents the market operation and the platform which occupies the fourth layer of the P2P-ETS architecture presented in Chapter 2. Some pilot P2P-ETS projects and platforms are currently being trialed in several countries. This includes the Piclo in the UK [33], Vandebron in the Netherlands [31], SonnenCommunity in Germany [32], and the Brooklyn microgrid in the US [36]. Some of these projects fit into four P2P-ETS platform models [45]; the retail supplier platform, vendor platform, community MG platform and blockchain[1] platform models.

Piclo and Vandebron demonstrate/utilise online platforms that allow prosumers to select and track the source of the energy they buy. Both platforms act as energy suppliers that provide incentive tariffs for consumers and generators to exchange energy. They are good examples of the retail supplier platform model as they allow suppliers to benefit by gaining better awareness of their customers and also obtain more value from their DER. This is achieved using algorithms to match local generation and consumption and provide data visualisation and analytics to customers [128]. SonnenCommunity is developed by Sonnen in Germany. This pilot project is similar to Piclo and Vandebron, but with more utilisation of storage systems for battery owners [32]. SonnenCommunity is an example of the vendor platform model[2]. The Brooklyn Microgrid is a network of Brooklyn residents and business owners who support local PV energy

[1]blockchain involves a block of data (transaction) interlocked to the previous block in the chain. It is a type of distributed ledger (database) that comprises of immutable, digitally recorded data in a block stored linearly [157].

[2]vendor platform allows exchange of energy between producers and consumers and the owner of the platform gets a commission for every sale.

generation and consumption. The Brooklyn P2P-ETS platform aims to allow social factor inclusion, encouraging generous prosumers with surplus energy donates energy to low-income households [45][158]. With the use of a blockchain model to provide secure decentralised protocols for managing and executing transactions through its smart contracts, the Brooklyn project fits into the community and the blockchain P2P-ETS platform models.

Other P2P-ETS platforms have been researched. One such method is the "Elecbay" for P2P-ETS in a grid-connected MG. The Elecbay is a software platform on which peers trade energy with others. Energy is listed for sale by energy sellers, energy buyers can browse the items, i.e. surplus energy and then place orders. Each order contains information about the time period for the energy exchange, the amount of energy, the price of the energy and details about the seller and buyer, e.g. identities and ratings of the reliability of energy supplied [128].

However, as noted in Ofgem report [57] in Chapter 2, 66.48% of an electricity bill is service charge, with approximately 24% related to network characteristics including distance charge. Distance and location of trading peers is an important factor in matching producer to consumer as highlighted in Chapter 3. Most of the pilot projects and P2P-ETS platforms discussed have been designed to match peers for trading energy using matching resources, preferences and objectives such as minimum cost, price and profits. Although local energy generation and consumption is investigated in [159], no demonstration of its implementation was discussed. Study [160] reported a local energy market with aim to maximise the utilisation of DER in a specific geographic area but the impact of distance charge was not assessed. Thus, this chapter considers distance as a major factor in matching peers for energy trading on the P2P-ETS platforms. A software platform is developed to support the pairing or matching interaction between energy traders. A case study based on real microgrid data is used to verify the performance of the platform and demonstrate potential increase in local energy consumption. Simulation results show that the developed platform is able to balance local generation and consumption, increase savings for local energy traders and reduce exchange between the prosumers and the utility grid. The remaining sections of this chapter are organised as follows: The developed platform is introduced in Section 6.1 which follows closely to the P2P-ETS prospect discussed in Chapter 2, the market bids and matching algorithm is presented in Section 6.2. The performance evaluation of the platform is discussed in Section 6.3. Section 6.4 presents the interface of the developed platform, while Section 6.5 summarises the chapter and draws conclusions.

6.1 The P2P-ETS Platform Design

To enable information exchange among peers and to facilitate the monitoring of the distribution network by the utility operators, a software based P2P-ETS platform is actively needed. The various actors that could interact on the platform has been discussed in Chapter 2. However, the actors used in this chapter are limited to producers, consumers and the utility grid[3]. Fig. 6.1 illustrates interactions on the platform. The energy consumption and generation of each prosumer is recorded by their smart meters. The smart meters also facilitate communication with the platform. The distribution network is an integral part of the platform, that delivers energy to the appropriate actor. The DSO is also grouped as an energy producer on the platform. The profiling of each prosumer detailing their preferences including energy price, quantity and location is stored on the platform. Data routing among the participants on the platform is as described in Chapter 3. The platform allows both the producers and the

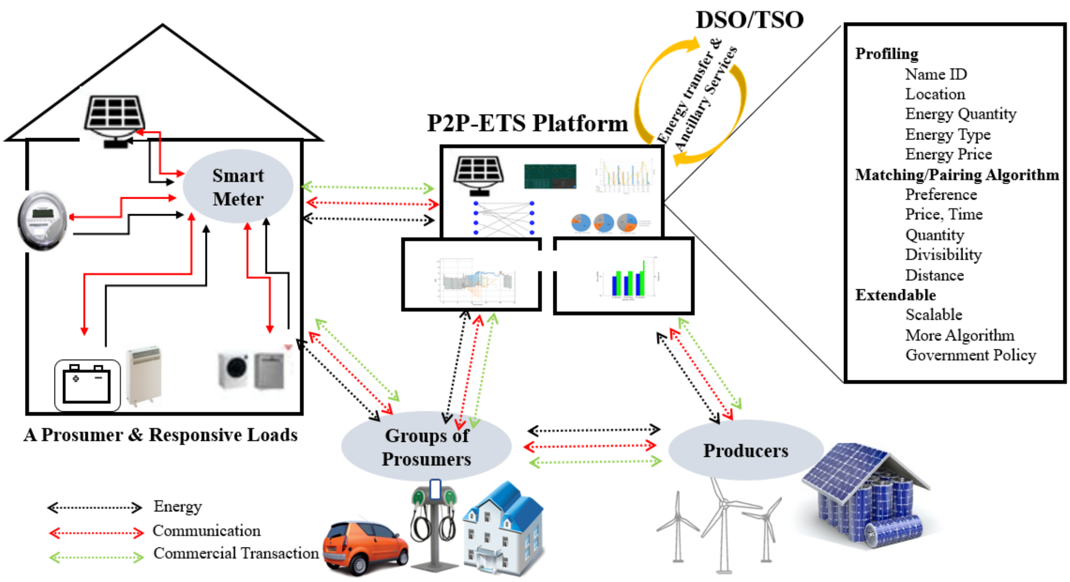

FIGURE 6.1: Interactions of producers and consumers on the P2P-ETS

[3]This is to provide a better understanding of the whole process, as the platform develops, other actors can easily be incorporated.

consumers to place bids for day-ahead, based on flexibility, and offer prices, with sellers able to respond regarding when they are available and what services they can provide. This information, along with the distance constraints of the producers and consumers, is all taken into consideration[4] before the matching solution to the bids and offers is delivered. Each buyer bid will specify its maximum buy price and sellers will also submit their minimum sell price. Sellers who have some price flexibility won't have any visibility of the buyers price, so as not to influence their offer prices. Such a system creates the market drivers which can bring costs down. Thus, any successful energy trading deal within the maximum and the minimum is considered a savings to both parties. The reader should Recall that the flowchart of the processes involved on the platform has been discussed in Chapter 2 (2.5), but for brevity, more emphasis will be provided where appropriate.

6.2 Market bids and Matching Algorithm

To develop a P2P-ETS platform, the characteristics of the energy market is first considered. The market has three features; **(a)** the trade proceeds by matching and anonymous pairwise meetings with bargaining, **(b)** participants are asymmetrically informed about the value of the traded quantity, and **(c)** no new entrants are allowed once the market is opened for energy trading. Due to the disadvantages of a centralised infrastructure discussed in Chapter 2, a decentralised market is utilised, where there is no auctioneer or central body and transactions take place via pairwise meetings of participants.

6.2.1 The Trading period

In the existing electricity market, energy is bought and sold in 30 minutes intervals. This structure of the market is based on energy generation, consumption and price that can vary due to [161]:

- <u>environmental conditions:</u> since the energy generation focus is on renewable sources, weather conditions affect the generation output of

[4]This chapter models the exchange of energy demands requirement from the prosumers at the tertiary level of control without explicitly touching the physicality of the underlying distribution network such as power flow analysis.

PV panels, as well as wind turbines and other renewable sources. So a market based on PV panels might increase the trading period during the winter period, and those based on wind turbine might reduce trading period during a season with high winds;

- time of day: time of electricity usage also affects the market trading period. In the traditional electricity billing, off peak period usage between $11pm$ and $6am$ attracts less fee as compared to the peak period, between $4pm$ and $9pm$, attracting the highest fee [162]. In addition, time of day electricity production for PV panels are highest around noon, which calls for a period trading market;

- grid balancing: Finally, the grid must account for the peak and off-peak electricity consumption periods, and the peak and off-peak generation periods within the design of an energy trading market to enable the balancing of supply and demand.

This thesis adopts period-based energy trading, with trading executed at t period. Buyers and sellers submit bids (including the quantity of energy, and the maximum price to buy or minimum price to sell) into the market during each period t_1 against the next trading period t_2 for a day-ahead energy delivery. An example of a trading period is shown in Fig. 6.2. The

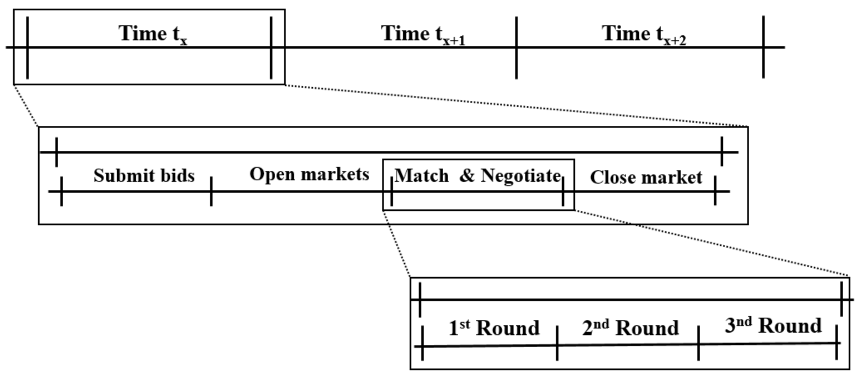

FIGURE 6.2: An illustration of the trading period on the P2P-ETS platform

activities at t_1 are divided into four-segments; submit bid, open market, match and negotiation, and close market including the settlement and market clearing. Once the market is opened, no more bids are submitted. The bids are matched using the matching algorithm presented in Chapter 3. The match and negotiation activities could proceed to several rounds depending on the number of players and the quantity of demand left in the market before proceeding to settlement and market clearing. An example of a bid structure is presented in Table 6.1, highlighting the quantity of energy

Quantity (kWh)	Price (p/kWh)	Actor ID	Actor Role
3.6	14.3	0	Consumer
1.8	12	1	Consumer
2	14.3	2	Consumer
4.2	13	3	Consumer
10	14.3	4	Grid
2	11	5	Producer
3	10	6	Producer
2.5	13	7	Consumer
4.5	10	8	Producer
3	9	9	Producer

TABLE 6.1: Market bid structure

demanded and supplied by the consumers and producers respectively, as well as the bid and offer prices.

6.2.2 The matching phase

After the bids have been submitted to the market, the participants are grouped into buyers and sellers. The quantity, price and distance preferences of the actors are used for an initial match utilising the matching algorithm as discussed in Chapter 3. The buyer's submitted price is the maximum price he is willing to pay for a $1kWh$ of energy, while the seller's submitted price is the minimum price he is willing to sell $1kWh$ of energy. Using Table 6.1 as reference, Consumer with ID 0, submitted a bid for $3.6kWh$ of energy with a maximum buy price of $14.3p/kWh$, whereas, Producer with ID 5, submitted a bid to sell $2kWh$ of energy with a minimum sell price of $11p/kWh$. For each actor to transact, the maximum price a buyer is willing to pay must be greater than the minimum price a seller is willing to sell. Then the bids are ranked in descending price order, while the offers are put in ascending price order to determine the equilibrium point where the social welfare[5] of the buyers and sellers can be maximised. An example of this association using the market bid structure presented in Table 6.1 is illustrated in Fig. 6.3. On the merit order[6], the equilibrium point for this particular scenario is at $13kWh$, occurring at a price of $12p/kWh$.

[5]the social welfare region illustrated in Fig. 6.3 is the region where any buyer would pay at most what he was willing to pay, and any sellers would receive at minimum the price he was willing to sell for.

[6]merit order is the ranking of the offers and bids.

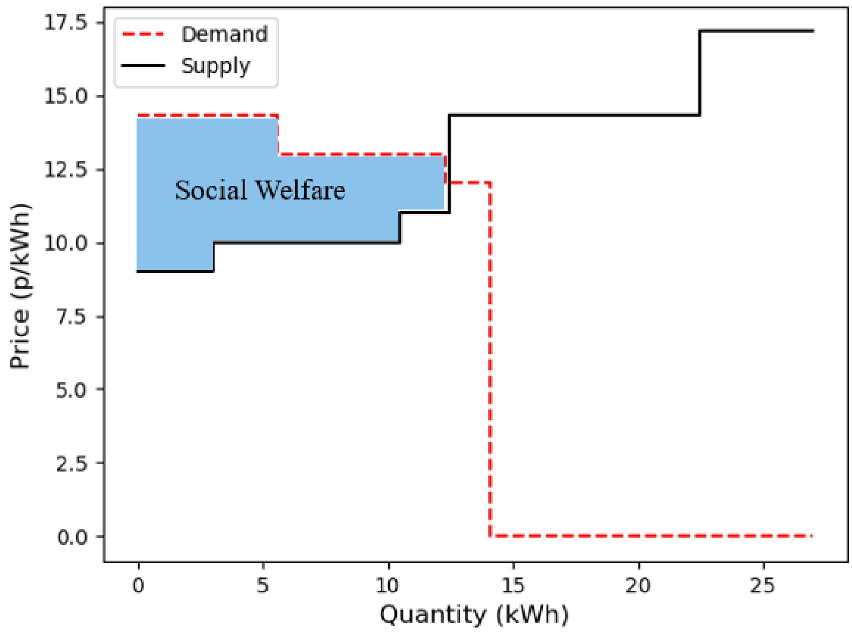

FIGURE 6.3: An illustration of the equilibrium price where social welfare can be optimised

This means that for an average household participating on the P2P-ETS platform would purchase $13kWh$ of energy at $12p/kWh$ instead of $14.3p/kWh$ offered by the grid. Thus saving a total of 16%[7]

On the P2P-ETS platform, buyers and sellers do not all meet simultaneously in a central market, rather each seller meets one buyer at a time and vice versa. To evaluate the benefits of local energy consumption, the matching algorithm is evaluated for two scenarios as:

- matching based on price and quantity: in this scenario, only price and quantity of energy preference of actors are considered in matching the sellers to the buyers[8];
- matching including distance: to evaluate the effect of distance on energy consumption, this scenario incorporated distance charge in the matching algorithm. As mentioned earlier in Chapter 2, for electricity, transmission losses and other associated costs are largely dependant on the distance travelled, making distance an important feature in this thesis.

[7]this cost reduction resulted from the diversity of the bid and offer price as well as the quantity of demand and supply.

[8]this is a reference scenario mostly adopted in the current electricity market system where choice over price is provided. Source of energy is partially incorporated.

6.2.3 The bargaining phase

During the bargaining phase, the two sets of groups are denoted by $N_{\bar{k}} = \{1, \cdots, n_{\bar{k}}\}$, where $\bar{k} = 1, 2$ denotes the type of group (buyers and sellers) and type $\bar{k}(n_{\bar{k}} \geq 1)$. When two actors from different groups N_1 and N_2 are matched, they bargain over the partition or all of the quantity(ies) associated with the match at that period. For instance, at time $t \in T$, let $i \in N_1$ and $j \in N_2$ be the initially matched prosumers. If a bilateral agreement is reached, the two bargaining partners leave the market with the agreed share of the unit price surplus. In the event of non-agreement, the algorithm proceeds to the next round (Fig. 6.2) and the remaining prosumers in the market are paired with new partners.

6.2.4 The Complete Market Mechanism

Bringing all of the market components together, the matching algorithm operates as follows.

1. Buyers and sellers submit bids to the market indicating their preferences relating to price of electricity and quantity demanded and supplied.
2. At each round, an initial match is established between a buyer and a seller;
   - for the case without distance charge, the initial match is based on the price and quantity preferences.
   - for the case with distance charge, the initial match is based on price, quantity of electricity and distance charge. In this scenario, the buyers and sellers are grouped based on their location (latitude and longitude). Each group has a distance charge. A buyer and seller that trade within their local group acquires no distance charge, compared to when the buyer and seller are located in different groups. An example is demonstrated in Fig. 6.4, with a distance charge of $2p/kWh, 4p/kWh, 6p/kWh$ for areas 1, 2, and 3 respectively.

3. The paired buyer and seller bargain, or negotiate on the price and quantity[9]. If a bilateral agreement is reached, the buyer and seller transact and leave the market with an equal share of the price surplus as cost savings[10], else another random match is performed with another partner in the next round.

4. If no agreement is reached within step **3**, the algorithm repeats from step **2**, until there are no more buyers in the market[11].

5. Equilibrium and payoffs are determined by the identity of the pairs that are matched and on their decision to trade or not[12].

6. Optimising the social welfare of the prosumers at the shaded region illustrated in Fig. 6.3 follows the optimisation problem presented in Chapter 5.

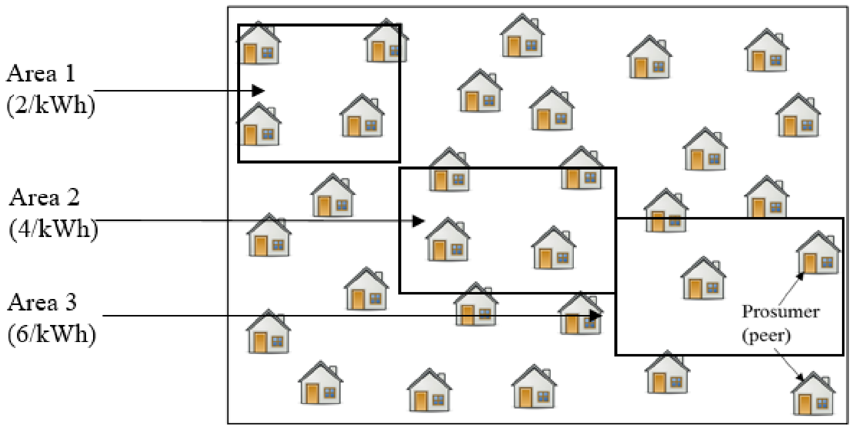

FIGURE 6.4: Local energy consumption, distance charge

The market mechanism is summarised in **Algorithm 1**.

[9]quantity of the energy demanded or supplied is divisible. This feature enables more autonomy to decide the quantity to sell or buy during the negotiation phase.

[10]for instance, if buyer A bid to pay maximum of 13p/kWh of energy, while seller D offers to sell for a minimum price of 10p/kWh of energy. After agreement and transaction, they both share a profit of 3p/kWh.

[11]All demands from the consumers are satisfied by one or more producers, however, some quantity of energy from the producers might remain in the market which is transferred to the next market bid period.

[12]for instance, if buyer A with bid 13p/kWh is paired with seller D with offer 10p/kWh. After agreement and transaction, they both share a savings of 3p/kWh. However, if seller D is paired with buyer C with bid 11p/kWh, then their shared savings would be 1p/kWh

Algorithm 4: The Market Mechanism Algorithm

```
Function TransactionArray (addsale);
Input  : buyers; sellers; bids price; offers price; quantity; distance charge
Output: sales amount; payoffs
Open market
for each buyer i in buyers do
    for each seller j in sellers do
        for each matched i and j do
            if distance charge i > distance charge j then
                bid i = bid i * distance charge
                offer j = offer j * distance charge
            end
            if distance charge i = distance charge j then
                no change to bid i and offer j
            end
            if bid price i ≥ offer price j && j quantity > 0 then
                calculate sales price
            end
            if j quantity ≥ i quantity then
                calculate sales quantity
            end
            calculate sales payoffs/savings
            optimise social welfare
            update addsale
        end
    end
end
Submit successful sales
Return to open market
```

6.3 Simulation and Result Analysis

To assess the performance of the algorithm and the platform, the platform development is based on python programming language. For autonomy, the prosumers determine the selling and buying prices of their energy per kWh and they decide on whether to accept a sale, or otherwise. A case of 10 prosumers is evaluated based on the market bid of Table 6.1. The demand requirement of the Consumers 0-3 are based on real energy demand data from the 'PECAN street project' [163]. The data set from 'PECAN street project' is for residential households and covers a variety of residential load patterns such as lighting, washing machine and air conditioning (a/c) systems etc, which are used at variable times. As with realistic power distribution system, the household profiles in the data set varies because the residence schedule/consumption are different from each other. The average peak solar PV output is about $0.4kWh$, the load demand by residential households will determine which household is willing to buy or sell energy. An instance of the data is presented in Fig. 6.5. P_{load} represents the energy

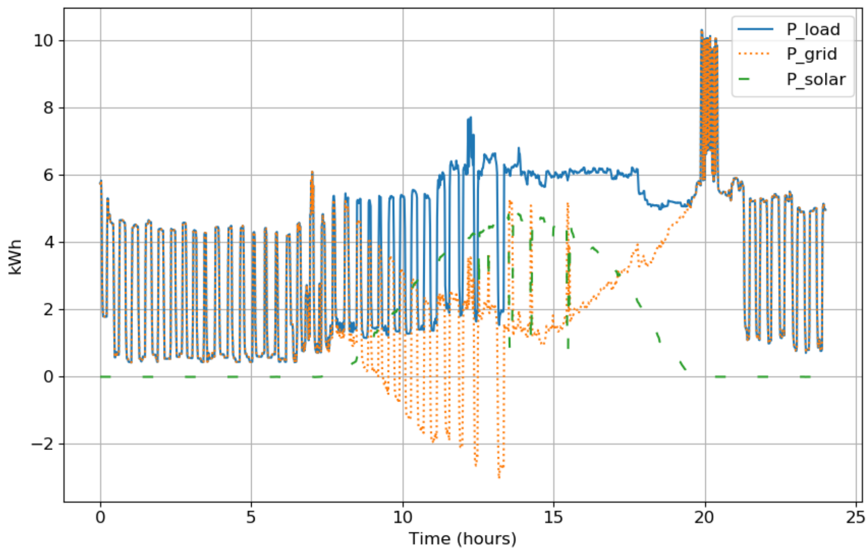

FIGURE 6.5: An instance of real energy profile of a house used alongside other households in the cases considered

consumption of the house, P_{grid} is the energy from the grid to balance the consumption, while P_{solar} is the energy generated over a 24hr period by the solar PV panels installed on the household roof. Between the hours of $0:00-9:00$, the energy consumption for the household is delivered from the grid between the hours of $9:00-20:00$, the generated solar energy increased sufficiently so that the household energy is mostly delivered from the solar panels, whilst the energy consumed during the remaining hours of the day is delivered from the grid. The total energy received from the grid is the energy submitted as a bid to the market for P2P trade with other prosumers (i.e., Consumer 0 profile). In addition, the advertised energy price for the grid is based on the average electricity price for households in the UK.While this work is motivated by geographical distance charges as this is an essential parameter in electricity billing and loses, transmission charges are motivated by the distance charge already discussed in Section 6.2.4

6.3.1 Scenario 1: Matching Based on Price and Quantity of Energy

This section considers the initial matching of prosumers on the platform based on their bid and offer price as well as quantity demanded and supplied. The result is analysed based on the energy demand and supply, and the cost saved by the prosumers.

6.3.1.1 Energy Demand and Supply on the P2P-ETS Platform

Fig. 6.6 shows an example of the matched pairs and the amount of energy

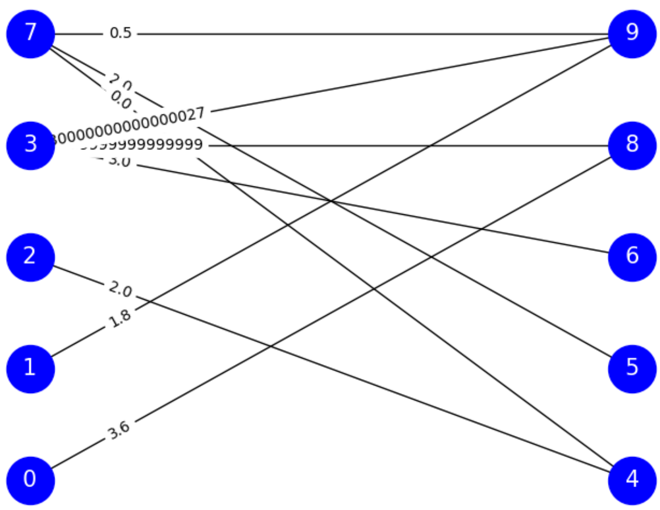

FIGURE 6.6: A graph illustrating the paired pairs and the amount of energy traded between them.

traded between each pair. It can be observed that due to the divisibility of the demands, some pairs, i.e., seller 9, participated in 3 rounds with 3 different paired buyers (1,3, and 7). Fig. 6.7 shows the result after energy has been traded. In the first round, Consumer 0 bought all its quantity demanded from Producer 8, similarly, Consumer 1 from Producer 9, and Consumer 2 from Grid 4. Producer 5 sold all its energy surplus to Consumer 7, as Producer 6 to Consumer 3. In the second round, the demand requirements of Consumer 3 has not been met, thus, Consumer 3 is paired with Producer 8. Producer 8 sold all its remaining energy to Consumer 3, while Consumer 7 purchased the remaining energy demands from Producer 9. Further, the market interactions proceed to round 3, where the remaining demand requirements of Consumer 3 is met by Producer 9.

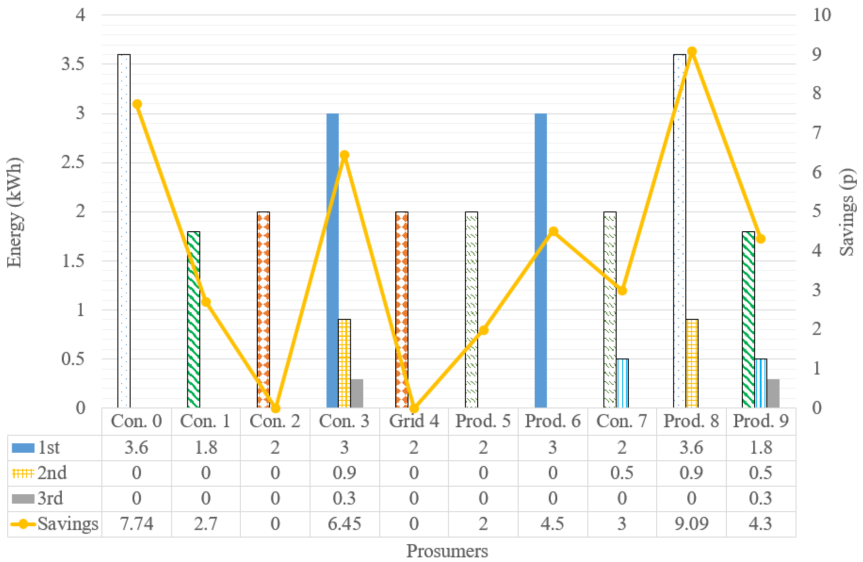

FIGURE 6.7: An illustration of the energy traded between pairs and individual cost savings

6.3.1.2 Cost Savings by the Prosumers on the P2P-ETS Platform

As discussed, the cost savings calculation is based on the price difference of the matched partners that traded energy. For instance, Consumer 0's $3.6kWh$, with a maximum buy price of $14.3p/kWh$ is supplied by Producer 8 with a minimum sale price of $10p/kWh$. Difference in the price equals $4.3p/kWh$, which would be shared as savings for both parties. Thus total savings of Consumer 0 by buying $3.6kWh$ of energy from the P2P platform is $7.74p$. This experience relates to other prosumers on the P2P-ETS platform. However, the maximum and minimum buy and sell price for Consumer 2 and Grid 4 is $14.3p/kWh$, thus, both parties when paired did not earn any savings. The

Qty. (kWh)	Price (p/kWh)	Actor ID	Actor Role	Cost Savings (p)
3.6	14.3	0	Consumer	7.74
1.8	12	1	Consumer	2.7
2	14.3	2	Consumer	0
4.2	13	3	Consumer	6.45
10	14.3	4	Grid	0
2	11	5	Producer	2
3	10	6	Producer	4.5
2.5	13	7	Consumer	3
4.5	10	8	Producer	9.09
3	9	9	Producer	4.3

TABLE 6.2: Market bid structure and cost savings for scenario 1

cost savings is illustrated in Table 6.2. In addition, it is worth noting that although the Grid has the highest amount of energy to sell in the market, it was only able to sell just $2kWh$ of its total energy, $10kWh$. This is as a result of its minimum sell price, which is higher than most of the consumers' maximum buy price. As shown from the equilibrium plot of Fig. 6.3 ($13kWh$ at $12p$), that on average, the consumers are able to save 16% of their cost on every kWh bought, while producers made a profit of 123% by participating on the P2P-ETS as compared to feeding the excess PV generation to the grid at a price of $5.38p/kWh$.

6.3.2 Scenario 2: Matching Based on Price, Quantity and Distance

In this section, the effect of the distance charge is assessed using the segmentation shown in Fig. 6.4. The market bid is as shown in Table 6.3, including the location of each prosumer on the platform. The results is presented based on the energy demanded and supplied, as well as the cost saved by the prosumers.

6.3.2.1 Energy Demand and Supply on the P2P-ETS Platform

Fig. 6.8 shows the result after energy has been traded. In the first round, Consumer 0 bought all of its demanded quantity from Producer 8, as Consumer 1 from Producer 9. Producer 5 sold all its energy surplus to

Qty. (kWh)	Price (p/kWh)	Dist. C (p/kWh)	Actor ID	Actor Role	Lat.	Long.	Savings (p)
3.6	14.3	2	0	Con.	53.4741	-2.2422	7.74
1.8	12	4	1	Con.	53.4595	-2.2412	4.50
2	14.3	2	2	Con.	53.4901	-2.2339	1.86
4.2	13	4	3	Con.	53.4668	-2.2464	9.75
10	14.3	6	4	Grid	53.4854	-2.2702	0.0
2	11	4	5	Prod.	53.4731	-2.2401	2.0
3	10	2	6	Prod.	53.4669	-2.2339	7.50
2.5	13	4	7	Con.	53.4601	-2.2394	3.50
4.5	10	2	8	Prod.	53.4705	-2.2394	9.99
3	9	2	9	Prod.	53.4755	-2.2402	7.86

TABLE 6.3: Market bid structure and cost savings for scenario 2

Consumer 7, as Producer 6 to Consumer 3. Interestingly, Consumer 2 was paired with the Grid 4, but as the asking price was high due to the distance charge, no trade occur between them. In the second round, the demand requirements of Consumer 3 were not met, thus, Consumer 3 was paired with Producer 8. Producer 8 sold all its remaining energy to Consumer 3, while Consumer 2's demand requirements were met by Producer 9. Grid 4 was paired with Consumer 7, but no trade occurred between them because of the high asking price and the distance charge. Further, the market interaction proceed to round 3, where the remaining demand requirements of Consumer 7 was met by Producer 9.

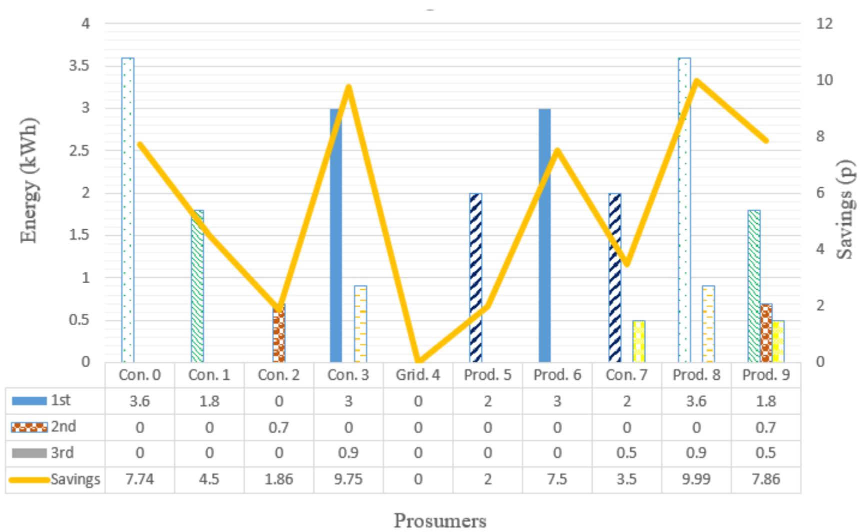

FIGURE 6.8: An illustration of the energy traded between pairs and individual cost savings

6.3.2.2 Cost Savings by the Prosumers on the P2P-ETS Platform

Similarly, using the cost savings calculations in Section 6.3.1.2, the total cost savings of Consumer 0 by buying $3.6kWh$ of energy from Producer 8 on the P2P-ETS platform is $7.74p$. The costs savings for other prosumers on the P2P-ETS platform is shown in Table 6.3. However, the maximum and minimum buy and sell price for Consumer 2 and Grid 4 is $14.3p/kWh$, but because they are located at different areas with different distance charge, when the two were paired, no trade occur. In addition, the grid was paired with Consumer 7 in the second round, however, no trade occur between them. Thus, the Grid did not earn any savings during the P2P market transactions. It can be observed that while Consumer 2 did not earn any savings in the first scenario because of the paired partner (Grid), he was able to earn a total savings of $3.71p$ in this scenario, as a result of being paired with a producer with lower asking price. These results show that consumers of local energy consumption acquired more cost savings than prosumers that do not trade energy locally.

6.3.3 Scenario 3: Impact of Ratio of Producers to Consumers and Scalability Assessment

Additional assessment was carried out to evaluate the performance and scalability of the P2P-ETS platform to varying ratios of sellers to buyers on the platform. A range of representative values of demands, supplies and

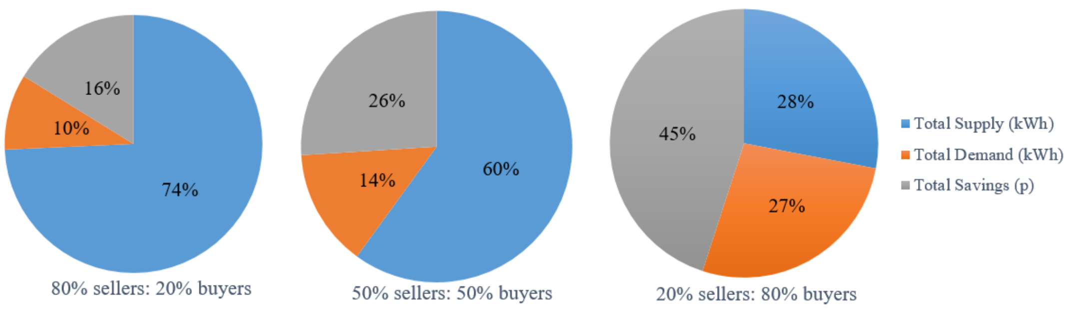

FIGURE 6.9: A pie chart showing the relationship between the total supply, demand and savings for different ratio of prosumers

price were assigned to the prosumers. For the buyers, minimum offer price is set between $11 - 14p/kWh$, quantity of energy demand is set to $1 - 5kWh$, while sellers bid price is set to $10 - 15p/kWh$ and quantity of energy supplies is set to $5 - 10kWh$. Simulations were run for different ratio of sellers to buyers for 30 participants. Fig. 6.9 shows the relationship between the total supply, demand and cost savings against varying ratios of prosumers. It can be observed that with a ratio of 80% of sellers to 20% of buyers, the total supply increased with less demand, compared to when there are 20% of sellers on the platform, as the total cost savings are a reflection of the volume of trade that occur on the platform. With 80% sellers, the savings is 16%, compared to 20% sellers and 45% cost savings. This result emphasises the importance of a P2P exchange of energy, the more the local demand is met by the local supply, the higher the community cost savings.

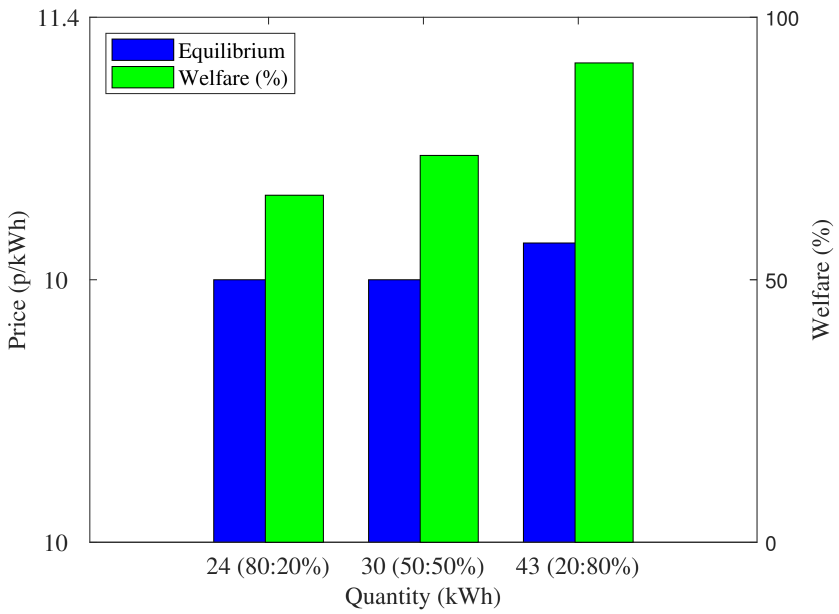

FIGURE 6.10: Relationship between the equilibrium price, quantity and the percentage welfare for different ratio of prosumers

Similarly, Fig. 6.10 shows the relationship between the equilibrium price, quantity and the percentage of the maximum welfare against the ratio of prosumers on the platform. It can be observed that for 80% of sellers, the average quantity traded is $24kWh$ at an equilibrium price of $10p/kWh$. However, with 50% of sellers, the traded quantity increased to $30kWh$ which reflects the increase in demand due to the increased number of buyers. In addition, with more buyers on the platform (80%), the traded quantity increased ($43kWh$) as well as the equilibrium price ($11p/kWh$). This reflects an economic market where an increase in demand and decrease in supply leads to increase in price of the commodity. Finally, we can observe from the plot that the percentage welfare of the participants increases as the ratio of buyers increases on the platform.

6.4 P2P-ETS Platform Interface

The developed platform interface is shown in Figs. 6.11, 6.12, 6.13 and Fig. 6.14. Fig. 6.11

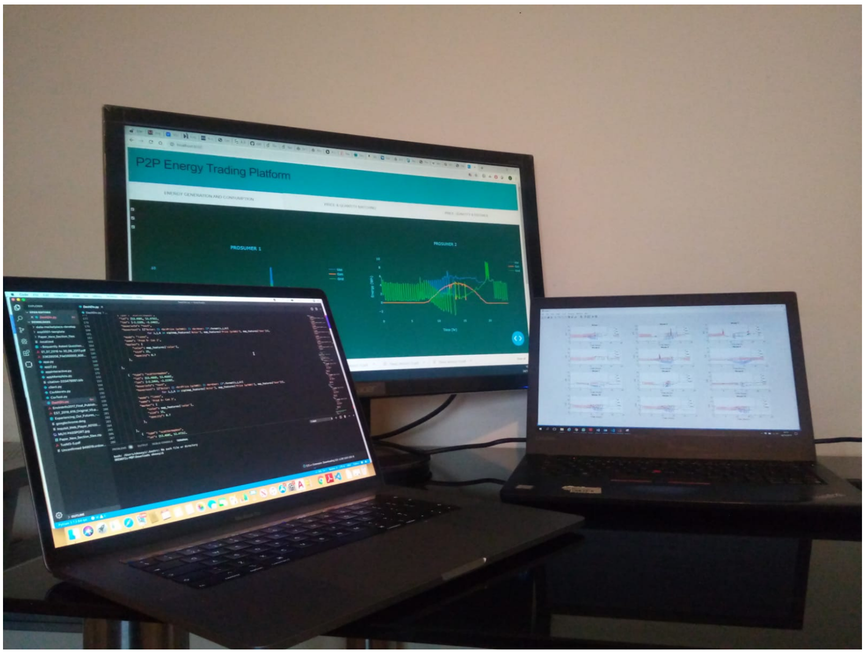

FIGURE 6.11: P2P-ETS platform set-up with connected devices

shows the overall setup of the connected devices representing prosumer smart meters on the P2P-ETS platform. Fig. 6.12 shows the received energy profile of the participants on the P2P platform. This details their energy generated, consumed and the energy received from the grid as represented in Fig. 6.5.

Similarly, Fig. 6.13 shows the bid submitted to the market and the location of the market participants on the map. The submitted bid is as represented in Table 6.3 and the plot as shown in Fig. 6.8. Fig. 6.13 shows the energy transfer between those that traded, as well as the links connecting them on the map.

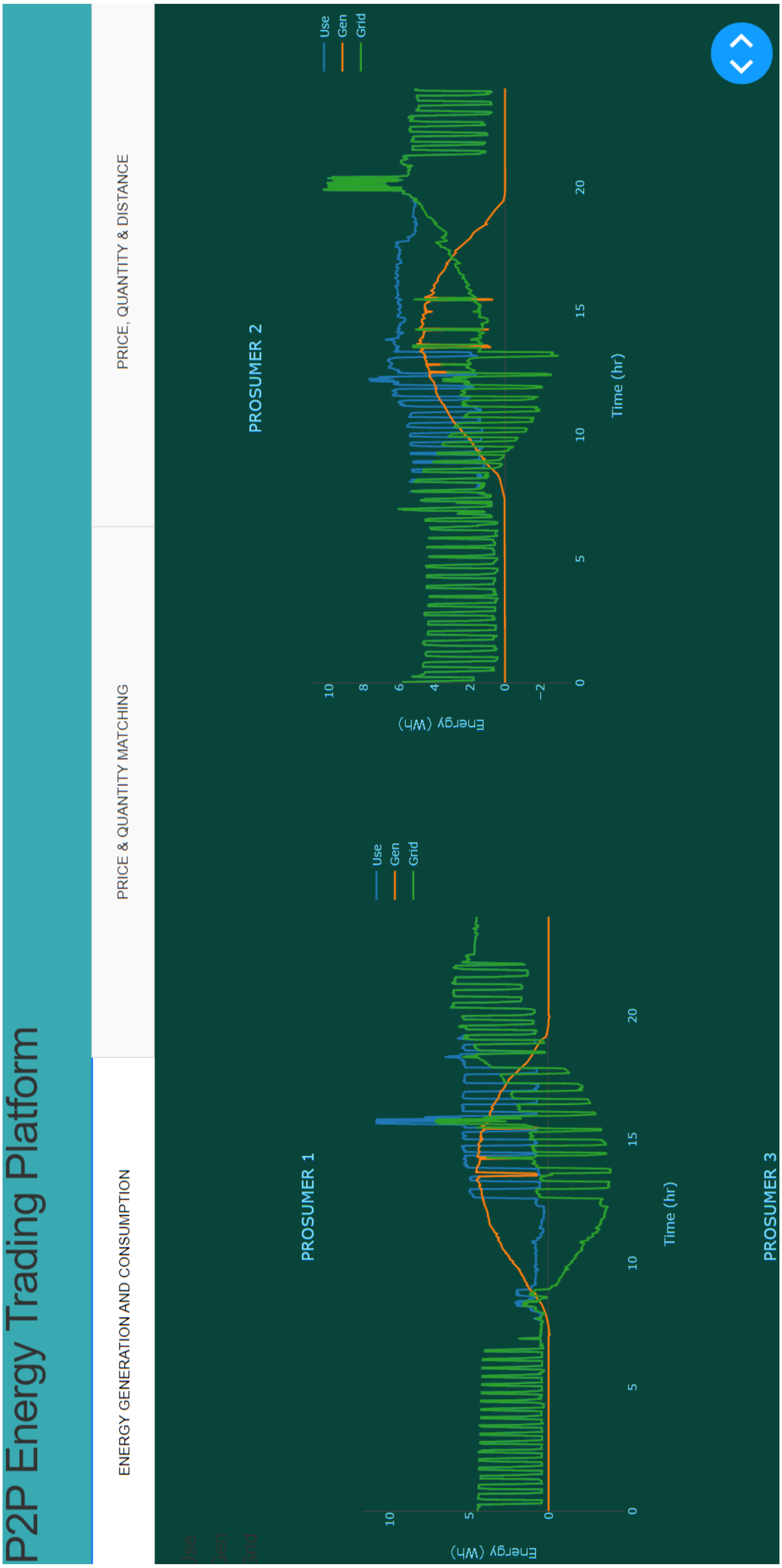

FIGURE 6.12: Prosumers profiling on the P2P-ETS platform

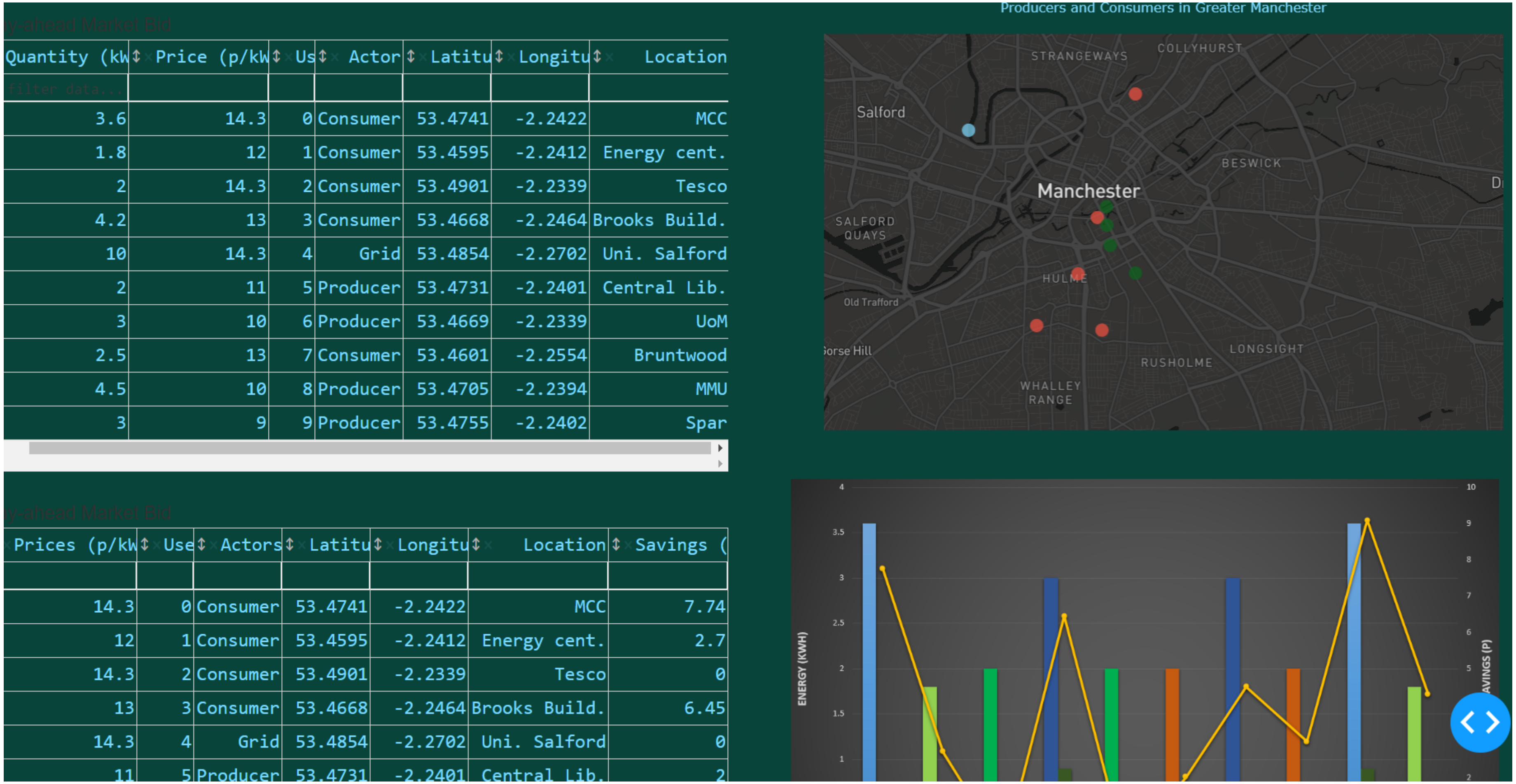

FIGURE 6.13: Market bid and the prosumers's location on the P2P-ETS platform

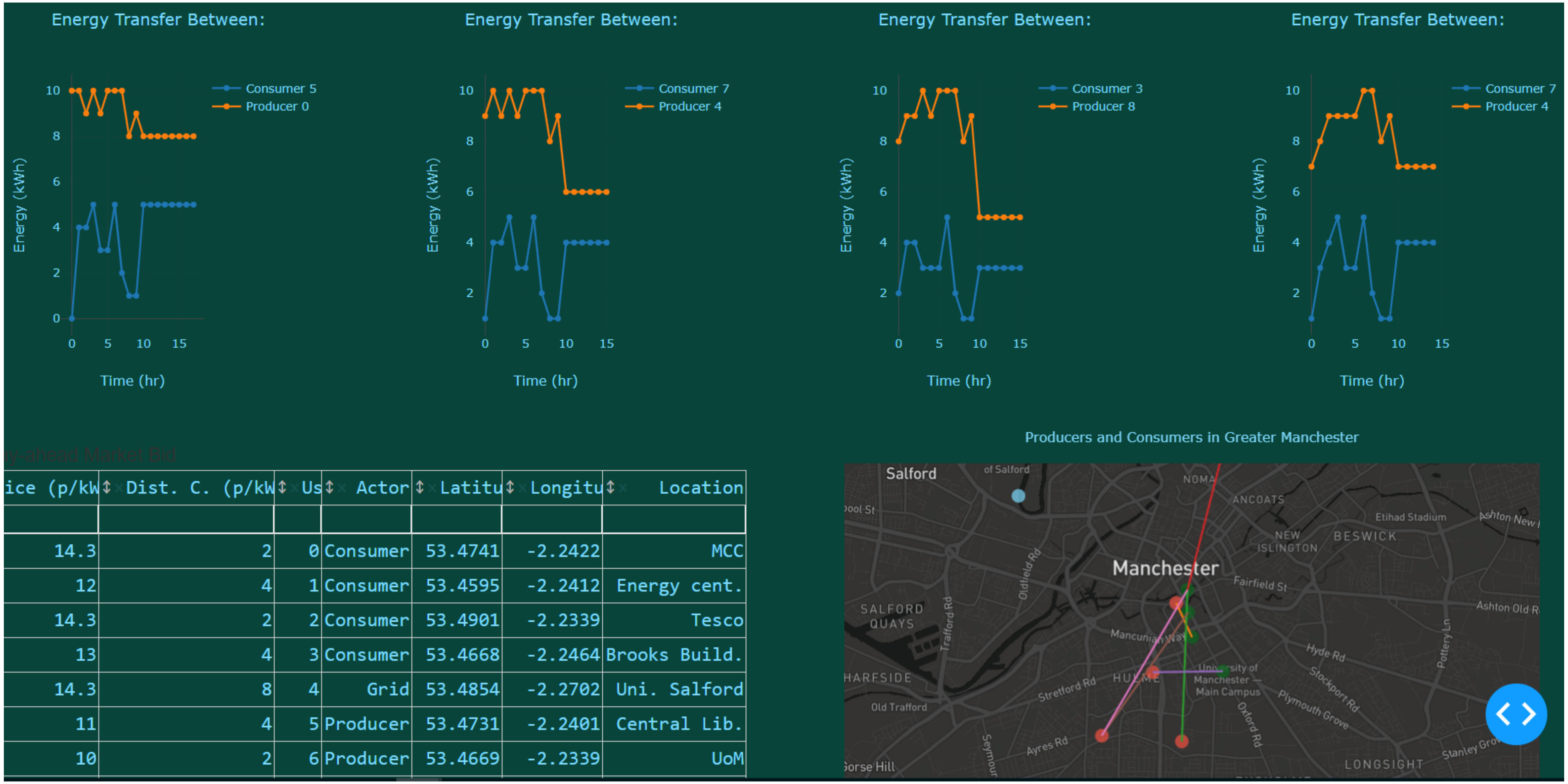

FIGURE 6.14: Energy transfer between prosumers and links connecting trading pairs

6.5 Chapter Summary

This chapter discussed the developed P2P-ETS platform. A case of local energy consumption was evaluated on the P2P-ETS platform using the algorithms derived from previous chapters. The chapter commenced with a description of the platform design showing the interaction between the actors on the platform. Then the market mechanism used on the platform was discussed for the two cases considered giving a snapshot of the developed platform interface. Simulation results indicate that local energy trading is not only beneficial to the environment, but also leads to a significant amount of savings by the trading partners of up to 45%, depending upon the number of participants and their ratios on the platform.

Chapter 7

Conclusions and Recommendations

THE conclusions drawn from the presented research work in the previous chapters are summarised. Limitation of the thesis are outlined. Possible future works are suggested.

7.1 Conclusion

AS the sharing economy becomes a *fait accompli*, where households can monetise existing assets, increase market competition and improve resource efficiency, its application within the smart grid has already begun in communities around the world. With the complexity associated with energy distribution networks, this thesis developed distributed algorithms and a P2P-ETS platform to manage and coordinate the large influx of DER as well as the altruistic goal of the diverse energy producers and consumers. To further understand this emerging P2P-ETS concept, Chapter 2 was dedicated to motivation, technologies and frameworks to enable P2P-ETS. The chapter discussed the various motivational factors for the actors participating on the P2P-ETS platform, ranging from profit optimisation, improved system efficiency and environmental benefits. The enabling technologies are further discussed including MGs, ESS and ICT. In addition, the required frameworks involving the trading structure, operation mechanism and optimisation to realise the P2P-ETS was discussed. Lastly, Chapter 2 concludes with a proposal of a four-layered architectural model to categorise the individual components and technologies involved in P2P-ETS.

Building further on the paradigm of the relation between shortest path problems, genetic algorithms and their application to smart grid, Chapter 3 presented a slime mould-inspired approach for optimised path between prosumers and consumers on the P2P-ETS platform. The chapter began by investigating the role of the optimised path between trading peers, with discussion on the traditional algorithms solving the problem. It was discovered that these optimised path algorithms have excessive computational time especially in a large network. Thus, the chapter introduced a genetic algorithm, in particular, slime mould dynamics. The slime mould solution is further extended to maximise flow capacity in the distribution networks and energy demand matching between prosumers based least cost distance metrics. The solutions presented therein can be used for congestion control on distribution links, provide alternate paths in cases of disruption on the optimal path and pairing of prosumers to implement local energy consumption or trading to further reduce cost and emissions loss.

In order to route information among the distributed trading peers on the P2P-ETS platform, Chapter 4 developed a DAP routing algorithm. Particularly, the DAP algorithm is analysed over imperfect communication network links such as probability of signal loss, message delay, congestion and different network topologies. The algorithm minimises both the communication delay and the loss of energy transaction messages that may result due to sub-optimal network conditions. The results show that the proposed routing algorithm is robust to packet loss on the communication links with a 20% reduction in delay compared with the hop-by-hop adaptive link state routing algorithm.

Chapter 5 of this project developed DDG algorithm to solve the EDP and minimises the energy generation cost whilst ensuring that total generated energy satisfies the total energy demand in the network. With performance evaluated over realistic network conditions like time-varying network delay and lossy communication links, the results suggest that by optimising individual energy generators to meet the aggregate network demand, additional costs due to energy storage may be eliminated. The proposed solution is extended to realise the global utility maximisation among market-based participants to reduce the overall costs and maintain fairness of all generators and demands. Further results suggest that traders with higher willingness to trade energy achieve higher utility. Also, there is reduction in quantity of energy demanded when the price of supply is high, but the price paid is dependent on the ratio of producers to consumers in the network. This utility maximisation algorithm is used to maximise the social welfare of participants on the P2P-ETS platform.

Summing together all of the distributed algorithms from previous chapters, Chapter 6 developed a market based negotiation P2P-ETS platform. Utilising the developed matching algorithm, consumers are paired with producers based on their preferences (price, quantity and distance). After the pairing, the pairs demonstrated autonomy by negotiating with their partners the price and quantity of energy to trade in a P2P fashion. If an agreement is reached and all demands are met, the pairs transact energy and exit the market, else, they proceed to the next round with new partners. The performance of the platform is evaluated with a case of local energy consumption using real microgrid data. The results show that local energy traders acquired more cost savings than prosumers that do not trade energy locally. However, the degree of the cost savings is dependent on the prosumers' paired partner and agreement on the platform, as well as the ratio of participants' demography, which can realise prosumer cost savings of 45%.

The conclusions of this thesis are as follows.

- Realisation of P2P-ETS is dependent on some enabling technologies including, energy generators, storage systems and information and communication technology.
- An optimised path between energy trading peers is actively needed to realise reduction in emissions and energy costs, implement local energy trade and to provide alternate paths for energy distribution in cases of disruption on the optimal path.
- In implementing distributed algorithms for P2P-ETS, communication constraints are major performance inhibitors that required robust techniques to mitigate it.
- Autonomy, preferences and welfare maximisation are additional motivation factors for prosumers to participate in P2P-ETS.
- Local energy consumption on a P2P-ETS platform could result in cost savings of up to 45% for participants of the platform.

- The demography of participants on the P2P-ETS platform determines the benefits acquired by the community on the platform. For instance, the higher the number of sellers (quantity supplied > demand), the lower the price of energy, the lower the percentage welfare (a function of sales), then the lower the cost savings (function of sales) on the P2P-ETS platform.

7.2 Limitations and Future work

There are two limitations identified in this thesis that could be addressed as a future research; security and data analytics.

The dynamicity of the energy market with penetration of distributed prosumers, deployment of smart metering and sensing facilities, foster P2P-ETS. As seen from the thesis, such P2P interactions requires complex data exchanges among the peers, utility grid and the market operators. This inevitably introduces security and privacy challenge in the existing system. For instance, entities trading energy needs to authenticate each other, ensure the integrity of messages sent/received, and ensure the privacy of personal data, including smart meter data. Though security was mentioned as a component of the P2P-ETS architectural model, it's detailed analysis was not given in this thesis. However, blockchain technology is evolving as a trustless framework for energy trading in smart grid to support real-time security and transaction management. The applicability of blockchain technology to P2P-ETS has been assessed within this research and earlier reported in [157]. An extension of the assessment is a possible future direction to ensure data integrity, privacy and authentication during and after energy exchange.

Secondly, the increasing integration of DER to the grid increases the challenge in balancing energy supply and demand. This directly affects the reliability of the power system due to the unexpected changes resulting from the addition of excess produced energy to the grid by the DER. Thus affecting other services like quality and continuity of service to the consumers. Albeit, if the influx of energy generation and consumption is not properly monitored to predict future inflow to the grid, engaging in P2P-ETS would be a challenge. This is because a prosumer energy profile might not be properly represented, and the amount of energy promised might be misleading or falsified. Artificial intelligence techniques such as machine learning and big data analytics could be used to identify consumer energy patterns and therefore enable tailored and value added energy products provision to achieve demand-side flexibility and energy trading. Machine learning techniques can be used to predict future behaviour of large sets of prosumers and market operatives, by assessing prosumers's uncertainty and correctly predicting their future behaviour regarding power consumptions and generations. Thus, the area of machine-learning techniques applied within P2P-ETS is another research future work. It will enable effective monitoring of the trustworthiness of prosumers data, to predict solar energy system performance and analysis of large data sets, thus increasing energy data trustworthiness for P2P-ETS.

Bibliography

[1] P. De Martini, K. M. Chandy, and N. Fromer, "Grid 2020: Towards a policy of renewable and distributed energy resources", *California Institute of Tech. Resnick Institute, Tech. Rep.*, 2012.

[2] Y. F. Eddy, H. B. Gooi, and S. X. Chen, "Multi-agent system for distributed management of microgrids", *IEEE Trans. on Power. Syst.*, vol. 30, no. 1, pp. 24–34, 2015, ISSN: 0885-8950.

[3] Y. Luo, S. Itaya, S. Nakamura, and P. Davis, "Autonomous cooperative energy trading between prosumers for microgrid systems", in *IEEE LCN Workshops*, 2014, pp. 693–696, ISBN: 1479937843.

[4] J. Matamoros, D. Gregoratti, and M. Dohler, "Microgrids energy trading in islanding mode", in *IEEE SmartGridComm*, 2012, pp. 49–54, ISBN: 1467309109.

[5] H. K. Nunna and S. Doolla, "Multiagent-based distributed-energy-resource management for intelligent microgrids", *IEEE Trans. on Ind. Electrons.*, vol. 60, no. 4, pp. 1678–1687, 2013, ISSN: 0278-0046.

[6] M. Fathi and H. Bevrani, "Statistical cooperative power dispatching in interconnected microgrids", *IEEE Trans. on Sustainable Energy*, vol. 4, no. 3, pp. 586–593, 2013, ISSN: 1949-3029.

[7] I. S. Bayram, M. Z. Shakir, M. Abdallah, and K. Qaraqe, "A survey on energy trading in smart grid", in *IEEE GlobalSIP*, 2014, pp. 258–262, ISBN: 1479970883.

[8] K. A. Nigim and W.-J. Lee, "Micro grid integration opportunities and challenges", in *Power Engineering Society General Meeting*, IEEE, 2007, pp. 1–6.

[9] O. Jogunola, A. Ikpehai, K. Anoh, B. Adebisi, M. Hammoudeh, S.-Y. Son, and G. Harris, "State-of-the-art and prospects for peer-to-peer transaction-based energy system", *Energies*, vol. 10, no. 12, p. 2106, 2017.

[10] K. Anoh, B. Adebisi, O. Jogunola, and M. Hammoudeh, "Cooperative hybrid wireless-powerline channel transmission for

peer-to-peer energy trading and sharing system", in *Proc. Intl. Conf. Future Netw. Distr. Syst.*, ACM, 2017, p. 7.

[11] O. Jogunola, B. Adebisi, K. Anoh, A. Ikpehai, M. Hammoudeh, G. Harris, and H. Gacanin, "Distributed adaptive primal algorithm for p2p-ets over unreliable communication links", *Energies*, vol. 11, no. 9, p. 2331, 2018.

[12] N. Liu, X. Yu, C. Wang, C. Li, L. Ma, and J. Lei, "Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers", *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3569–3583, 2017.

[13] Y. A. Sha'aban, A. Ikpehai, B. Adebisi, and K. M. Rabie, "Bi-directional coordination of plug-in electric vehicles with economic model predictive control", *Energies*, vol. 10, no. 10, p. 1507, 2017.

[14] S. Magnússon, P. C. Weeraddana, and C. A. Fischione, "Distributed approach for the optimal power-flow problem based on admm and sequential convex approximations", *IEEE Trans. Contr. Netw. Syst.*, vol. 2, no. 3, pp. 238–253, 2015.

[15] Z. Zhang and M. Y. Chow, "Convergence analysis of the incremental cost consensus algorithm under different communication network topologies in a smart grid", *IEEE Trans. Power Syst.*, vol. 27, no. 4, pp. 1761–1768, 2012.

[16] J. Wu, T. Yang, D. Wu, K. Kalsi, and K. H. Johansson, "Distributed optimal dispatch of distributed energy resources over lossy communication networks", *IEEE Trans. Smart Grid*, vol. 8, no. 6, pp. 3125–3137, 2017.

[17] T. Yang, J. Lu, D. Wu, J. Wu, G. Shi, Z. Meng, and K. H. Johansson, "A distributed algorithm for economic dispatch over time-varying directed networks with delays", *IEEE Trans. Ind. Electron.*, vol. 64, no. 6, pp. 5095–5106, 2017.

[18] Z. Zhang and M.-Y. Chow, "The influence of time delays on decentralized economic dispatch by using incremental cost consensus algorithm", in *Contr. Optimization Methods for Electric Smart Grids*, vol. 371, Springer-Verlag, 2012, pp. 313–326.

[19] T. Yang, D. Wu, Y. Sun, and J. Lian, "Impacts of time delays on distributed algorithms for economic dispatch", in *IEEE Power Energy Society General Meeting*, 2015, pp. 1–5.

[20] Z. Zhang, X. Ying, and M.-Y. Chow, "Decentralizing the economic dispatch problem using a two-level incremental cost consensus algorithm in a smart grid environment", in *NAPS*, IEEE, 2011, pp. 1–7.

[21] McKinsey, *Global energy perspective: Reference case 2018*, Accessed: 2018-02-20, 2017. [Online]. Available: `http://www.elder.org.tr/Content/yayinlar/Global_Energy_Perspective_Reference_Case_2018_vP.pdf`.

[22] T. Guardian, *Venezuela blackout has killed 21 people, opposition leaders say*, Accessed: 2019-03-20, 2019. [Online]. Available: `https://www.theguardian.com/world/2019/mar/11/venezuela-blackout-deaths-latest-news-caracas-opposition-claims-`.

[23] O. Jogunola, A. Ikpehai, K. Anoh, B. Adebisi, M. Hammoudeh, H. Gacanin, and G. Harris, "Comparative analysis of p2p architectures for energy trading and sharing", *Energies*, vol. 11, no. 1, p. 62, 2017.

[24] Y. Wu, X. Tan, L. Qian, and D. H. Tsang, "Optimal management of local energy trading in future smart microgrid via pricing", in *INFOCOM WKSHPS*, IEEE, 2015, pp. 570–575.

[25] A. Sergaki and K. Kalaitzakis, "A knowledge management platform for supporting smart grids based on peer to peer and service oriented architecture technologies", in *Intl. Conf. SMFG*, IEEE, 2011, pp. 154–159.

[26] S. A. A. Kazmi, M. K. Shahzad, A. Z. Khan, and D. R. Shin, "Smart distribution networks: A review of modern distribution concepts from a planning perspective", *Energies*, vol. 10, no. 4, p. 501, 2017.

[27] O. Jogunola, W. Wang, and B. Adebisi, "Slime mould-inspired path optimisation and prosumers matching algorithm in peer-to-peer energy trading", *Energies (To be submitted)*, 2019.

[28] O. Jogunola, K. Anoh, B. Adebisi, A. Ikpehai, M. Hammoudeh, and G. Harris, "Economic dispatch, resource allocation and utility maximisation of energy prosumers in smart grid", *Applied Energy, Elsevier (Under review)*, 2019.

[29] O. Jogunola, Y. Tsado, and B. Adebisi, "Peer-to-peer energy trading platform: A case of local energy consumption", *Energies (To be submitted)*, 2019.

[30] R. Green, "Competition in generation: The economic foundations", *Proc. of the IEEE*, vol. 88, no. 2, pp. 128–139, 2000.

[31] Vandebron, *Step up to good energy*, Accessed: 2017-06-26, 2015. [Online]. Available: `http://www.vandebron.nl/`.

[32] SonnenCommunity, *Sonnen*, Accessed: 2017-06-26, 2017. [Online]. Available: `http://www.sonnenbatterie.de/en/sonnenCommunity/`.

[33] Open-Utility, *Introducing piclo*, Accessed: 2017-06-26, 2016. [Online]. Available: `http://www.openutility.com/piclo/`.

[34] J. Cao and M. Yang, "Energy internet–towards smart grid 2.0", in *IEEE ICNDC*, 2013, pp. 105–110, ISBN: 1479930466.

[35] IEEE-Spectrum, *Enerchain: A decentralized market on the blockchain for energy wholesalers*, Accessed: 2017-06-26, 2017. [Online]. Available: `http://spectrum.ieee.org/energywise/energy/the-smarter-grid/enerchain-a-decentralized-market-on-the-blockchain-for-energy-wholesalers`.

[36] Brooklynmicrogrid, *Step up to good energy*, Accessed: 2017-06-26, 2017. [Online]. Available: `http://brooklynmicrogrid.com/`.

[37] E. Hausman, R. Hornby, and A. Smith, "Bilateral contracting in deregulated electricity markets", *The American Public Power Association, Synapse Energy Economics, Tech. Rep*, 2008.

[38] A. Belgana, B. P. Rimal, and M. Maier, "Multi-objective pricing game among interconnected smart microgrids", in *IEEE PES General Meeting/Conf. & Exposition*, 2014, pp. 1–5, ISBN: 1479964158.

[39] Q. Jiang, M. Xue, and G. Geng, "Energy management of microgrid in grid-connected and stand-alone modes", *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 3380–3389, 2013, ISSN: 0885-8950.

[40] Y. Zhang, N. Gatsis, and G. B. Giannakis, "Robust energy management for microgrids with high-penetration renewables", *IEEE Trans, on Sustainable Energy*, vol. 4, no. 4, pp. 944–953, 2013, ISSN: 1949-3029.

[41] X. Kong, L. Bai, Q. Hu, F. Li, and C. Wang, "Day-ahead optimal scheduling method for grid-connected microgrid based on energy storage control strategy", *J. Modern Power Syst. and Clean Energy, Springer*, vol. 4, no. 4, p. 648, 2016, ISSN: 2196-5420.

[42] Z. Ding, W.-J. Lee, and J. Wang, "Stochastic resource planning strategy to improve the efficiency of microgrid operation", *IEEE Trans. on Ind. Appl.*, vol. 51, no. 3, pp. 1978–1986, 2015, ISSN: 0093-9994.

[43] W.-Y. Chiu, H. Sun, and H. V. Poor, "Energy imbalance management using a robust pricing scheme", *IEEE Trans. on Smart Grid*, vol. 4, no. 2, pp. 896–904, 2013, ISSN: 1949-3053.

[44] I. C. Paschalidis, B. Li, and M. C. Caramanis, "Demand-side management for regulation service provisioning through internal pricing", *IEEE Trans. on Power Syst.*, vol. 27, no. 3, pp. 1531–1539, 2012, ISSN: 0885-8950.

[45] T. Morstyn, N. Farrell, S. J. Darby, and M. D. McCulloch, "Using peer-to-peer energy-trading platforms to incentivize prosumers to form federated power plants", *Nature Energy*, vol. 3, no. 2, p. 94, 2018.

[46] C. Sijie and L. Chen-Ching, "From demand response to transactive energy: State of the art", *J. Modern Power Syst. and Clean Energy, Springer*, vol. 5, no. 1, pp. 10–19, 2017.

[47] T. Zhu, Z. Huang, A. Sharma, J. Su, D. Irwin, A. Mishra, D. Menasche, and P. Shenoy, "Sharing renewable energy in smart microgrids", in *ACM/IEEE ICCPS*, 2013, pp. 219–228.

[48] A. Ikpehai, B. Adebisi, and K. M. Rabie, "Broadband plc for clustered advanced metering infrastructure (ami) architecture", *Energies*, vol. 9, no. 7, p. 569, 2016.

[49] M. R. Alam, M. St-Hilaire, and T. Kunz, "An optimal p2p energy trading model for smart homes in the smart grid", *Energy Efficiency, Springer*, pp. 1–19, 2017, ISSN: 1570-646X.

[50] K. M. Tsui and S.-C. Chan, "Demand response optimization for smart home scheduling under real-time pricing", *IEEE Trans. on Smart Grid*, vol. 3, no. 4, pp. 1812–1821, 2012, ISSN: 1949-3053.

[51] T. G. Hovgaard, S. Boyd, L. F. Larsen, and J. B. Jørgensen, "Nonconvex model predictive control for commercial refrigeration", *Intl. J. Control, Taylor & Francis*, vol. 86, no. 8, pp. 1349–1366, 2013, ISSN: 0020-7179.

[52] Z. Wang and L. Wang, "Intelligent negotiation agent with learning capability for energy trading between building and utility grid", in *IEEE ISGT Asia*, 2012, pp. 1–6, ISBN: 1467312207.

[53] F. De Angelis, M. Boaro, D. Fuselli, S. Squartini, F. Piazza, and Q. Wei, "Optimal home energy management under dynamic electrical and thermal constraints", *IEEE Trans. on Ind. Informatics*, vol. 9, no. 3, pp. 1518–1527, 2013, ISSN: 1551-3203.

[54] H. Bilil, G. Aniba, and M. Maaroufi, "Multiobjective optimization of renewable energy penetration rate in power systems", *Energy Procedia, Elsevier*, vol. 50, pp. 368–375, 2014, ISSN: 1876-6102.

[55] D. Zhang, S. Liu, and L. G. Papageorgiou, "Fair cost distribution among smart homes with microgrid", *Energy Conversion and Management, Elsevier*, vol. 80, pp. 498–508, 2014, ISSN: 0196-8904.

[56] T. Liu, X. Tan, B. Sun, Y. Wu, X. Guan, and D. H. Tsang, "Energy management of cooperative microgrids with p2p energy sharing in distribution networks", in *IEEE SmartGridComm*, 2015, pp. 410–415, ISBN: 1467382892.

[57] ofgem, *Breakdown of an electricity bill*, Accessed: 2019-06-22, 2018. [Online]. Available: https://www.ofgem.gov.uk/data-portal/breakdown-electricity-bill.

[58] E. S. Trust, *Smart export guarantee and feed-in tariffs*, Accessed: 2019-07-20, 2019. [Online]. Available: https://www.energysavingtrust.org.uk/renewable-energy/electricity/solar-panels/smart-export-guarantee-and-feed-tariffs.

[59] ofgem, *Upgrading our energy system smart systems and flexibility plan*, Accessed: 2019-06-20, 2017. [Online]. Available: https://www.ofgem.gov.uk/system/files/docs/2017/07/upgrading_our_energy_system_-_smart_systems_and_flexibility_plan.pdf.

[60] Gov.Uk, *Uk becomes first major economy to pass net zero emissions law*, Accessed: 2019-07-20, 2019. [Online]. Available: https://www.gov.uk/government/news/uk-becomes-first-major-economy-to-pass-net-zero-emissions-law.

[61] E. Department for Business and I. Strategy, *Uk energy in brief 2019*, Accessed: 2019-08-01, 2019. [Online]. Available: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/819511/UK_Energy_in_Brief_2019.pdf.

[62] A. Bani-Ahmed, L. Weber, A. Nasiri, and H. Hosseini, "Microgrid communications: State of the art and future trends", in *ICRERA*, IEEE, 2014, pp. 780–785.

[63] R. G. Pratt, P. J. Balducci, C. Gerkensmeyer, S. Katipamula, M. C. Kintner-Meyer, T. F. Sanquist, K. P. Schneider, and T. J. Secrest, "The smart grid: An estimation of the energy and co2 benefits", Pacific Northwest National Lab.(PNNL), Richland, WA (United States), Tech. Rep., 2010.

[64] M. A. Ahmed, Y. C. Kang, and Y. C. Kim, "Communication network architectures for smart-house with renewable energy resources", *Energies*, vol. 8, no. 8, pp. 8716–8735, 2015, ISSN: 1996-1073. DOI: 10.3390/en8088716.

[65] Y. Kabalci, "A survey on smart metering and smart grid communication", *Renewable and Sustainable Energy Reviews*, vol. 57, pp. 302–318, 2016.

[66] V. C. Gungor, D. Sahin, T. Kocak, S. Ergut, C. Buccella, C. Cecati, and G. P. Hancke, "A survey on smart grid potential applications and communication requirements", *IEEE Trans. ind. informatics*, vol. 9, no. 1, pp. 28–42, 2013.

[67] M. Kuzlu, M. Pipattanasomporn, and S. Rahman, "Communication network requirements for major smart grid applications in han, nan and wan", *Computer Networks*, vol. 67, pp. 74–88, 2014.

[68] R. H. Khan and J. Y. Khan, "A comprehensive review of the application characteristics and traffic requirements of a smart grid communications network", *J. Comput. Networks, Elsevier*, vol. 57, no. 3, pp. 825–845, 2013, ISSN: 1389-1286. DOI: 10.1016/j.comnet.2012.11.002.

[69] I. Atzeni, L. G. Ordóñez, G. Scutari, D. P. Palomar, and Fonollosa, "Demand-side management via distributed energy generation and storage optimization", *IEEE Trans. on Smart Grid*, vol. 4, no. 2, pp. 866–876, 2013, ISSN: 1949-3053.

[70] J. Rajasekharan and V. Koivunen, "Cooperative game-theoretic approach to load balancing in smart grids with community energy storage", in *IEEE EUSIPCO*, 2015, pp. 1955–1959, ISBN: 0992862639.

[71] Y. Tsado, D. Lund, and K. A. Gamage, "Resilient communication for smart grid ubiquitous sensor network: State of the art and prospects for next generation", *Computer Communications*, vol. 71, pp. 34–49, 2015.

[72] A. H. Jaafar, A. Rahman, A. Mohiuddin, and M. Rashid, "Modelling of an advanced charging system for electric vehicles", in *IOP Conf. Series: Materials Science and Engineering*, IOP Publishing, vol. 184, 2017, p. 012 023.

[73] J. Kang, R. Yu, X. Huang, S. Maharjan, Y. Zhang, and E. Hossain, "Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains", *IEEE Trans. Ind. Informatics*, vol. 13, no. 6, pp. 3154–3164, 2017.

[74] R. Alvaro-Hermana, J. Fraile-Ardanuy, P. J. Zufiria, L. Knapen, and D. Janssens, "Peer to peer energy trading with electric vehicles", *IEEE Intell. Transp. Syst. Mag.*, vol. 8, no. 3, pp. 33–44, 2016, ISSN: 1939-1390.

[75] B. Al-Omar, A. Al-Ali, R. Ahmed, and T. Landolsi, "Role of information and communication technologies in the smart grid", *J. Emerging Trends in Comput. and Inf. Sciences*, vol. 3.7, pp. 707–716, 2012.

[76] A. Ikpehai and B. Adebisi, "6loplc for smart grid applications", in *IEEE ISPLC*, 2015, pp. 211–215.

[77] R. H. Khan and J. Y. Khan, "A comprehensive review of the application characteristics and traffic requirements of a smart grid communications network", *J. Comput. Networks, Elsevier*, vol. 57, no. 3, pp. 825–845, 2013, ISSN: 1389-1286. DOI: 10.1016/j.comnet.2012.11.002.

[78] C. Cano, A. Pittolo, D. Malone, L. Lampe, A. M. Tonello, and A. G. Dabak, "State of the art in power line communications: From the applications to the medium", *IEEE J. Selected Areas in Commun.*, vol. 34, no. 7, pp. 1935–1952, 2016.

[79] G. López, J. Matanza, D. de la Vega, M. Castro, A. Arrinda, J. I. Moreno, and A. Sendin, "The role of power line communications in the smart grid revisited: Applications, challenges, and research initiatives", *IEEE Access*, 2019.

[80] E. Ancillotti, R. Bruno, and M. Conti, "The role of communication systems in smart grids: Architectures, technical solutions and research challenges", *Computer Commun., Elsevier*, vol. 36, no. 17-18, pp. 1665–1697, 2013, ISSN: 0140-3664. DOI: 10.1016/j.comcom.2013.09.004.

[81] T. Dragičević, P. Siano, S. Prabaharan, *et al.*, "Future generation 5g wireless networks for smart grid: A comprehensive review", *Energies*, vol. 12, no. 11, p. 2140, 2019.

[82] ITU-R, *Minimum requirements related to technical performance for imt-2020 radio interface(s)*, Accessed: 2019-08-20, 2017. [Online]. Available: https://www.itu.int/dms_pub/itu-r/opb/rep/R-REP-M.2410-2017-PDF-E.pdf.

[83] M. Donegan and J. Rogerson, *What is 5g and where is it available in the uk?*, Accessed: 2019-08-20, 2019. [Online]. Available: https://5g.co.uk/guides/what-is-5g/.

[84] D. Marabissi, L. Mucchi, R. Fantacci, M. Spada, F. Massimiani, A. Fratini, G. Cau, J. Yunpeng, and L. Fedele, "A real case of implementation of the future 5g city", *Future Internet*, vol. 11, no. 1, p. 4, 2019.

[85] F. Chowdhury and M. Kolberg, "Performance evaluation of structured peer-to-peer overlays for use on mobile networks", in *Sixth Intl. Conf. Developments in eSystems Engineering*, IEEE, 2013, pp. 57–62.

[86] N. J. Navimipour and F. S. Milani, "A comprehensive study of the resource discovery techniques in peer-to-peer networks", *Peer-to-Peer Networking and Applications*, vol. 8, no. 3, pp. 474–492, 2015.

[87] K. Shuaib, J. A. Abdella, F. Sallabi, and M. Abdel-Hafez, "Using blockchains to secure distributed energy exchange", in *IEEE 5th Intl. Conf. CoDIT*, 2018, pp. 622–627.

[88] D. Gregoratti and J. Matamoros, "Distributed energy trading: The multiple-microgrid case", *IEEE Trans. Ind. Electron.*, vol. 62, no. 4, pp. 2551–2559, 2015.

[89] C. Zhang, J. Wu, M. Cheng, Y. Zhou, and C. Long, "A bidding system for peer-to-peer energy trading in a grid-connected microgrid", *Energy Procedia, Elsevier*, vol. 103, pp. 147–152, 2016, ISSN: 1876-6102.

[90] W. Tushar, C. Yuen, D. B. Smith, N. U. Hassan, and H. V. Poor, "A canonical coalitional game theoretic approach for energy management for nanogrids", in *IEEE ISGT ASIA*, 2015, pp. 1–6, ISBN: 1509012389.

[91] A. Chis and V. Koivunen, "Coalitional game based cost optimization of energy portfolio in smart grid communities", *arXiv preprint arXiv:1705.04118*, 2017.

[92] D. Ilic, P. G. Da Silva, S. Karnouskos, and M. Griesemer, "An energy market for trading electricity in smart grid neighbourhoods", in *IEEE DEST*, 2012, pp. 1–6, ISBN: 1467317039.

[93] W. Inam, D. Strawser, K. K. Afridi, R. J. Ram, and D. J. Perreault, "Architecture and system analysis of microgrids with peer-to-peer electricity sharing to create a marketplace which enables energy access", in *IEEE ICPE-ECCE Asia*, 2015, pp. 464–469, ISBN: 8957082549.

[94] A. Y. Lam, L. Huang, A. Silva, and W. Saad, "A multi-layer market for vehicle-to-grid energy trading in the smart grid", in *IEEE INFOCOM WKSHPS*, 2012, pp. 85–90, ISBN: 1467310174.

[95] I. Lopez-Rodriguez and M. Hernandez-Tejera, "Infrastructure based on supernodes and software agents for the implementation of energy markets in demand-response programs", *Applied Energy, Elsevier*, vol. 158, pp. 1–11, 2015, ISSN: 0306-2619.

[96] I. Atzeni, L. G. Ordóñez, G. Scutari, D. P. Palomar, and J. R. Fonollosa, "Noncooperative and cooperative optimization of distributed energy generation and storage in the demand-side of the smart grid", *IEEE Trans. Signal Processing*, vol. 61, no. 10, pp. 2454–2472, 2013.

[97] N. Liu, X. Yu, C. Wang, C. Li, L. Ma, and J. Lei, "An energy sharing model with price-based demand response for microgrids of peer-to-peer prosumers", *IEEE Trans. on Power Syst.*, 2017, ISSN: 0885-8950.

[98] M. R. Alam, M. St-Hilaire, and T. Kunz, "A bi-linear optimization model for collaborative energy management in smart grid", in *IEEE ISGT-Europe*, 2016, pp. 1–6, ISBN: 1509033580.

[99] H. Neema, W. Emfinger, and A. Dubey, "A reusable and extensible web-based co-simulation platform for transactive energy systems", in *Trans. Energy Syst. and Workshop*, 2016.

[100] J. Lee, J. Guo, J. K. Choi, and M. Zukerman, "Distributed energy trading in microgrids: A game-theoretic model and its equilibrium analysis", *IEEE Trans. on Ind. Electron.*, vol. 62, no. 6, pp. 3524–3533, 2015, ISSN: 0278-0046.

[101] Y. Zhou, S. Ci, H. Li, and Y. Yang, "A new framework for peer-to-peer energy sharing and coordination in the energy internet", in *ICC Green Commun. Syst. and Networks Symp.*, IEEE, 2017.

[102] O. Jogunola, B. Adebisi, K. Anoh, A. Ikpehai, and M. Hammoudeh, "Adaptive routing algorithm for information management in distributed microgrids in smart grid", in *Proc. IFAC Workshop CSGRES*, IFAC, 2019.

[103] J. M. Guerrero, M. Chandorkar, T.-L. Lee, and P. C. Loh, "Advanced control architectures for intelligent microgrids—part i: Decentralized and hierarchical control", *IEEE Trans. on Ind. Electron.*, vol. 60, no. 4, pp. 1254–1262, 2013, ISSN: 0278-0046.

[104] J. M. Guerrero, P. C. Loh, T.-L. Lee, and M. Chandorkar, "Advanced control architectures for intelligent microgrids—part ii: Power quality, energy storage, and ac/dc microgrids", *IEEE Trans. on Ind. Electron.*, vol. 60, no. 4, pp. 1263–1270, 2013, ISSN: 0278-0046.

[105] M. Iqbal, M. Azam, M. Naeem, A. Khwaja, and A. Anpalagan, "Optimization classification, algorithms and tools for renewable energy: A review", *Renewable and Sustainable Energy Reviews, Elsevier*, vol. 39, pp. 640–654, 2014, ISSN: 1364-0321.

[106] S. Chen, N. B. Shroff, and P. Sinha, "Energy trading in the smart grid: From end-user's perspective", in *Asilomar Conf. on Signals, Syst. and Comput.*, IEEE, 2013, pp. 327–331.

[107] D. T. Nguyen and L. B. Le, "Optimal energy management for cooperative microgrids with renewable energy resources", in *IEEE Int. Conf. on SmartGridComm*, 2013, pp. 678–683.

[108] Z. Zhou, J. Bai, and S. Zho, "A stackelberg game approach for energy management in smart distribution systems with multiple microgrids", in *IEEE ISADS*, 2015, pp. 248–253, ISBN: 147998261X.

[109] W. Su and A. Q. Huang, "A game theoretic framework for a next-generation retail electricity market with high penetration of distributed residential electricity suppliers", *Applied Energy. Elsevier*, vol. 119, pp. 341–350, 2014, ISSN: 0306-2619.

[110] N. Zhang, Y. Yan, and W. Su, "A game-theoretic economic operation of residential distribution system with high participation of distributed electricity prosumers", *Applied Energy. Elsevier*, vol. 154, pp. 471–479, 2015, ISSN: 0306-2619.

[111] W. Saad, Z. Han, H. V. Poor, and T. Basar, "Game-theoretic methods for the smart grid: An overview of microgrid systems, demand-side management, and smart grid communications", *IEEE Signal Process. Magazine*, vol. 29, no. 5, pp. 86–105, 2012, ISSN: 1053-5888.

[112] F. Rahimi and F. Albuyeh, "Applying lessons learned from transmission open access to distribution and grid-edge transactive energy systems", in *IEEE Power & Energy Society Conf. ISGT*, IEEE, 2016, pp. 1–5.

[113] F. Rahimi, A. Ipakchi, and F. Fletcher, "The changing electrical landscape: End-to-end power system operation under the transactive energy paradigm", *IEEE Power and Energy Magazine*, vol. 14, no. 3, pp. 52–62, 2016.

[114] A. Sha and M. Aiello, "A novel strategy for optimising decentralised energy exchange for prosumers", *Energies*, vol. 9, no. 7, p. 554, 2016.

[115] C.-C.-E. S. G. C. Group, *Smart grid reference architecture*, Accessed: 2017-09-09, 2012. [Online]. Available: `https://ec.europa.eu/energy/sites/ener/files/documents/xpert_group1_reference_architecture.pdf`.

[116] Y. Zhou, S. Ci, H. Li, and Y. Yang, "A new framework for peer-to-peer energy sharing and coordination in the energy internet", in *IEEE. Intl. Conf. on Commun.*, IEEE, 2017, pp. 1–6.

[117] N. Atamturk and M. Zafar, "Transactive energy: A surreal vision or a necessary and feasible solution to grid problems", *California Public Utilities Commission Policy & Planning Division, Los Angeles*, 2014.

[118] N. Jiang, Y. Cheng, J. Zhou, T. Zhou, W. Xu, and D. Xu, "Toward biology-inspired solutions for routing problems of wireless sensor networks with mobile sink", *Soft Computing*, vol. 22, no. 23, pp. 7847–7855, 2018.

[119] X. Zhang, Q. Wang, F. T. Chan, S. Mahadevan, and Y. Deng, "A physarum polycephalum optimization algorithm for the bi-objective shortest path problem.", *Intl. J Unconventional Computing*, vol. 10, 2014.

[120] A. Ghasemkhani, A. Anvari-Moghaddam, J. M. Guerrero, and B. Bak-Jensen, "An efficient multi-objective approach for designing of communication interfaces in smart grids", in *IEEE PES ISGT-Europe*, IEEE, 2016, pp. 1–6.

[121] E. W. Dijkstra, "A note on two problems in connexion with graphs", *Numerische mathematik*, vol. 1, no. 1, pp. 269–271, 1959.

[122] R. Bellman, "On a routing problem", *Quarterly of applied mathematics*, vol. 16, no. 1, pp. 87–90, 1958.

[123] X. Zhang, Q. Wang, A. Adamatzky, F. T. Chan, S. Mahadevan, and Y. Deng, "An improved physarum polycephalum algorithm for the shortest path problem", *The Scientific World Journal*, vol. 2014, 2014.

[124] C. Gao, C. Yan, Z. Zhang, Y. Hu, S. Mahadevan, and Y. Deng, "An amoeboid algorithm for solving linear transportation problem", *Physica A: Statistical Mechanics and Its Applications*, vol. 398, pp. 179–186, 2014.

[125] Y.-P. Gunji, T. Shirakawa, T. Niizato, M. Yamachiyo, and I. Tani, "An adaptive and robust biological network based on the vacant-particle transportation model", *Journal of theoretical biology*, vol. 272, no. 1, pp. 187–200, 2011.

[126] C. Gao, S. Chen, X. Li, J. Huang, and Z. Zhang, "A physarum-inspired optimization algorithm for load-shedding problem", *Applied Soft Computing*, vol. 61, pp. 239–255, 2017.

[127] S. Hemalatha and P. Valsalal, "Identification of optimal path in power system network using bellman ford algorithm", *Modelling and Simulation in Engineering*, vol. 2012, p. 28, 2012.

[128] C. Zhang, J. Wu, Y. Zhou, M. Cheng, and C. Long, "Peer-to-peer energy trading in a microgrid", *Applied Energy*, vol. 220, pp. 1–12, 2018.

[129] L. Cuadra, M. Pino, J. Nieto-Borge, and S. Salcedo-Sanz, "Optimizing the structure of distribution smart grids with renewable generation against abnormal conditions: A complex networks approach with evolutionary algorithms", *Energies*, vol. 10, no. 8, p. 1097, 2017.

[130] P. Nguyen, W. Kling, and J. Myrzik, "Power flow management in active networks", in *Bucharest PowerTech*, IEEE, 2009, pp. 1–6.

[131] D. Sohier, G. Georgiadis, S. Clavière, M. Papatriantafilou, and A. Bui, "Physarum-inspired self-biased walkers for distributed clustering", in *Intl. Conf. Principles Of Distributed Syst.*, Springer, 2012, pp. 315–329.

[132] A. Tero, R. Kobayashi, and T. Nakagaki, "A mathematical model for adaptive transport network in path finding by true slime mold", *Journal of theoretical biology*, vol. 244, no. 4, pp. 553–564, 2007.

[133] X. Zhang and C. Yan, "Physarum-inspired solutions to network optimization problems", in *Shortest Path Solvers. From Software to Wetware*, Springer, 2018, pp. 329–363.

[134] L. Nian, W. Jie, and W. Lingfeng, "Distributed energy management for interconnected operation of combined heat and power-based microgrids with demand response", *J. Modern Power Syst. and Clean Energy*, vol. 5, no. 3, pp. 478–488, 2017.

[135] S. Yang, S. Tan, and J. X. Xu, "Consensus based approach for economic dispatch problem in a smart grid", *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4416–4426, 2013.

[136] A. Safdarian, M. Fotuhi-Firuzabad, and M. Lehtonen, "A distributed algorithm for managing residential demand response in smart grids", *IEEE Trans. Ind. Informatics*, vol. 10, no. 4, pp. 2385–2393, 2014.

[137] S. Bahrami, M. H. Amini, M. Shafie-khah, and J. P. Catalao, "A decentralized renewable generation management and demand response in power distribution networks", *IEEE Trans. Sust. Energy*, 2018.

[138] H. Wang and J. Huang, "Incentivizing energy trading for interconnected microgrids", *IEEE Trans. Smart Grid*, 2018.

[139] M. H. Amini, S. Bahrami, F. Kamyab, S. Mishra, R. Jaddivada, K. Boroojeni, P. Weng, and Y. Xu, "Decomposition methods for distributed optimal power flow: Panorama and case studies of the dc

model", in *Classical and Recent Aspects of Power Syst. Optimization*, Elsevier, 2018, pp. 137–155.

[140] P. P. Marino, *Optimization of Computer Networks: Modeling and Algorithms: a Hands-on Approach*. John Wiley & Sons, 2016.

[141] A. Lisser and P. Mahey, "Multicommodity flow problems and decomposition in telecommunications networks", in *Handbook of Optimization in Telecommunications*, Springer, 2006, pp. 241–267.

[142] M. Manfren, "Multi-commodity network flow models for dynamic energy management–mathematical formulation", *Energy Procedia*, vol. 14, pp. 1380–1385, 2012.

[143] R. S. Adhikari, N. Aste, and M. Manfren, "Multi-commodity network flow models for dynamic energy management–smart grid applications", *Energy Procedia*, vol. 14, pp. 1374–1379, 2012.

[144] K. Koushik, S. Saswati, and T. Leandros, "Optimization based rate control for multipath sessions", in *Teletraffic Science and Engineering*, vol. 4, Elsevier, 2001, pp. 805–816.

[145] N. Michael and A. Tang, "Halo: Hop-by-hop adaptive link-state optimal routing", *IEEE/ACM Trans. Network.*, vol. 23, no. 6, pp. 1862–1875, 2015.

[146] Net2plan, *Net2plan: The open-source network planner*, Accessed: 2018-04-26.

[147] S. Marzal, R. González-Medina, R. Salas-Puente, E. Figueres, and G. Garcerá, "A novel locality algorithm and peer-to-peer communication infrastructure for optimizing network performance in smart microgrids", *Energies*, vol. 10, no. 9, p. 1275, 2017.

[148] S. Boyd, L. Xiao, and A. Mutapcic, "Subgradient methods", *lecture notes of EE392o, Stanford University, Autumn Quarter*, vol. 2004, pp. 2004–2005, 2003.

[149] F. Al Farsi, M. Albadi, N. Hosseinzadeh, and A. Al Badi, "Economic dispatch in power systems", in *8th GCC Conf. & Exhibition*, IEEE, 2015, pp. 1–6.

[150] K. Anoh, D. Bajovic, D. Vukobratovic, B. Adebisi, D. Jakovetic, and M. Cosovic, "Distributed energy trading with communication constraints", in *IEEE PES ISGT-Europe*, Oct. 2018, pp. 1–6. DOI: `10.1109/ISGTEurope.2018.8571810`.

[151] D. P. Bertsekas, *Nonlinear programming*. Athena scientific Belmont, 1999.

[152] A. Nedic and A. Ozdaglar, "Distributed subgradient methods for multi-agent optimization", *IEEE Trans. Auto. Control*, vol. 54, no. 1, pp. 48–61, 2009.

[153] H. Terelius, U. Topcu, and R. Murray, "Decentralized multi-agent optimization via dual decomposition", in *18th IFAC World Congress, 28 Aug. 2011 - 2 Sept. 2011, Milano, Italy*, 2011, pp. 11 245–11 251.

[154] D. Blatt, A. O. Hero, and H. Gauchman, "A convergent incremental gradient method with a constant step size", *SIAM J. Optimization*, vol. 18, no. 1, pp. 29–51, 2007.

[155] F. Acciani, P. Frasca, G. Heijenk, and A. Stoorvogel, "Achieving robust average consensus over lossy wireless networks", *IEEE trans. control of network syst.*, pp. 1–1, 2018.

[156] R. Boas Jr, "Lhospital's rule without mean-value theorems", *The American Mathematical Monthly*, vol. 76, no. 9, pp. 1051–1053, 1969.

[157] O. Jogunola, M. Hammoudeh, B. Adebisi, and K. Anoh, "Demonstrating blockchain-enabled peer-to-peer energy trading and sharing", in *IEEE CCECE*, May 2019.

[158] E. Mengelkamp, B. Notheisen, C. Beer, D. Dauer, and C. Weinhardt, "A blockchain-based smart grid: Towards sustainable local energy markets", *Computer Science-Research and Development*, vol. 33, no. 1-2, pp. 207–214, 2018.

[159] S. Hall and K. Roelich, "Local electricity supply: Opportunities, archetypes and outcomes", 2015, *Infrastructure Business models, valuation and Innovation for Local Delivery*.

[160] C. Long, J. Wu, C. Zhang, L. Thomas, M. Cheng, and N. Jenkins, "Peer-to-peer energy trading in a community microgrid", in *2017 IEEE Power & Energy Society General Meeting*, IEEE, 2017, pp. 1–5.

[161] J. Park, R. Chitchyan, A. Angelopoulou, and J. Murkin, "A block-free distributed ledger for p2p energy trading: Case with iota?", in *Intl. Conf. Advanced Info. Syst. Engineering*, Springer, 2019, pp. 111–125.

[162] T. Telegraph, *New electricity tariff offers 80pc discount for night-time usage*, Accessed: 2019-07-26, 2017. [Online]. Available: `https://www.telegraph.co.uk/bills-and-utilities/gas-electric/new-electricity-tariff-offers-80pc-discount-night-time-usage/`.

[163] F. M. Uriarte, *Pecan street project field data*, Accessed: 2019-05-06, 2014. [Online]. Available: `https://sites.google.com/site/fabianuriarte/downloads`.